Recognition of Conative and Affective Behavior in Web Learning using Digital Gestures

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Abstract

It is reasonably easy to understand a student when in a classroom. Learners can be uniquely identified, content can be specifically presented, and advancement can be individually supervised, maintained, and reviewed on a regular basis. In addition, study has found that conventional classroom (mainly of cognitive type) solution, are not always workable in the online setting. Lately, companies offering web-learning courses often tend to elucidate on conative and affective attributes of learners. These attributes are more stable over different online learning circumstances. These companies are discovering the requirement to set their focal point on the conative and affective factors that influence learning. Many contemporary researchers have extended their research on learning and memory constructs (and associated measures) to include conative and affective but very few have successfully deciphered these perspectives into technology. Human gestures are nothing but psychosomatic motions, which evolve due to the communication between the mind and body. These Human gestures give rise to digital gestures in an online environment. Keyboard press, mouse movement, page tracking, hyperlink usage, scrolling rate etc. are some of the web usage characteristics. Web Mining is a way to search for "interesting" relationships in web data. It has immense potential in discovering some decisive knowledge like conative and affective elements that will help the company provide learners with better learning experience. Primarily they need to identify the dominant power of emotions and intentions on learning, and then, seek personalized solutions to revolutionize the presentation of learning. This paper highlights on how conative and affective attributes of a learner can be transformed to real-time data and analyzed using Web Mining. Finally, our approach would be to discover several learners with similar psychological characteristics and their grouping will help us achieve mass customization.

Keywords: Personalized Learning, Web Mining, Clustering

1. INTRODUCTION

The focus of this paper is how we can discover prime psychological attributes like conative (desires, intentions) and affective (emotions, feelings) behaviors in a complex system like the World Wide Web. We first try to understand the necessity of personalized learning. Then we explore the world of Digital gestures, which is an outcome of Web Mining combined with Data Mining to produce some interesting results about an individual or a group at large. We also draw a connection between the collected data and the psychological factors. The critical component of this analysis is how we can associate the behavior of numerous individuals and cluster them together to perform mass customization.

2. NEED FOR PERSONALIZED LEARNING

The Web offers the perfect technology and environment for personalized learning where learners can be uniquely identified, content can be specifically presented, and progress can be individually monitored, supported, and assessed. Technologically, researchers are making rapid progress towards personalized learning on the Web using object architecture and adaptive technology.

However, missing still is a whole-person understanding of how individuals learn online (more than just how they process, build, and store knowledge). Primarily cognitive solutions originally designed for the classroom solutions (and facilitated by instructors) are often not enough to meet the individual, sophisticated needs of Web learners.

3. RESEARCH ACTIVITIES: PAST AND PRESENT

We are still very much in the nascent stage for creating Web learning environments. More needs to be learnt about designing successful online environments, technically, pedagogically and personally. Some of the studies pertaining learning show an inclination towards personalized learning.

Reeves [1] advocated stronger, more reliable theoretical foundations in learning when he suggested, ‘much of the research in the field of computer-based instruction is pseudoscience because it fails to live up to the theoretical, definitional, methodological, and/or analytic demands of the paradigm upon which it is based’.

In contrast, conative and affective attributes of individuals are more stable over different online learning situations. Consequently, many Web learning designers are finding that conventional cognitive solutions are not enough. They are discovering the need to increase their focus on the conative and affective factors that influence learning. Any psychological decision is followed by a physical activity. In a

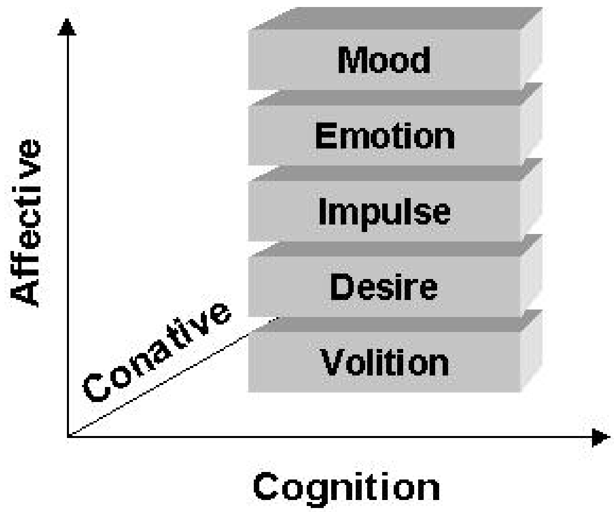

Figure 1: The information-processing model of cognition.

classroom, this can be observed when a student raises a spontaneous question or disagrees on a certain aspect.

There is a vital relationship between key psychological factors (conative, affective, cognitive, and social), which influence learning differently. There is a constant attempt to identify the critical links between Web learning environments, learning differences and learning ability. The web also supports learning methodologies that match individual learning differences. This form of learning system opens a new chapter in Web personalization.

Cronbach [2] found that learning could be more effective when the adaptive principle is used. So in the fifties, he challenged the field to find 'for each individual the treatment to which he can most easily adapt'. He emphasized that we should design treatments, not to fit the average person, but to fit groups of students with particular aptitude patterns.

In the late eighties, Snow [3] described how in cognitive psychology, conation as a learning factor has been 'demoted' and 'since it seems not really to be a separable function,' it is merged with affection. Snow was in search of an information-processing model of cognition that would include possible cognitive-conative-affective intersections. He was looking for a way to fit realistic aspects of mental life into instructional models. The information-processing model of cognition is illustrated in Figure 1. According to Snow [4], the best instruction involves treatments that differ in psychological structure and completeness and differential mental abilities. We should design treatments, not to fit the average person, but to fit groups of students with particular aptitude patterns. This is personalization or adaptive learning approach (called mass customization) that identifies aggregate types or segmented populations.

Meanwhile, many contemporary researchers have extended their research on learning and memory constructs (and associated measures) to include conative, affective and social influences [5] [6] [7] [8] [9] [10].

Still, most have done so without recognizing and incorporating the dominant influence of conative, affective, and social factors. As a result, powerful psychological factors, such as intentions, personal desire, will, striving, motivation, efficacy, collaboration, pride, fear, frustration and satisfaction, are still being ignored or demoted to a secondary role. The cognitive-rich tradition remains the dominant consideration for learning.

Web Technologists have to go further and build a system that recognizes psychological factors over a network. The task involves a study of web users with varying psychological attributes and technology to bring such concepts to life.

Digital gestures are one such attempt to realize some of the psychological factors based on the learner's mode of scanning. We should be aware that not all factors can be recognized. Psychological factors such as motivation and pride are not easy to grasp using simple digital gestures. A more complicated environment may be needed to apprehend those factors. Several research projects in the MITMedia Lab focus on Affective Computing.

4. DIGITAL GESTURES

4.1 Background

Every visit to a website generates important individual behavioral data, regardless of whether knowledge resources are used or not. Every individual's action is a digital gesture exhibiting habits, preferences, and tendencies [11]. These interactions reveal important trends and patterns that can help a company design a Web site based on the analyzed results. Web Learning organizations can seize this opportunity to aggregate, enhance, and mine Web data to learn more about their students.

Digital gestures work on the following principles:

- Information seeking mechanism on the Web based on modes of browsing and searching differentiated by information needs and information seeking activity.
- Operational methods for measuring information seeking on the Web by analyzing browser-based actions and events.
- Combinational use of multiple, complementary methods of collecting qualitative and quantitative data on how people seek and use Web-based information in their natural work settings.

4.2 Modes of Web Browsing Activities

Browsing

Directed browsing: This type of browsing occurs when browsing is systematic, focused, and directed by a specific object or target. Examples include scanning a list for a known item, and verifying information such as dates or other attributes.

Semi directed browsing: This occurs when browsing is predictive or generally purposeful. The target is less definite and browsing is less systematic. An example is entering a single, general term into a database and casually examining the retrieved records.

Undirected browsing: This occurs when there is no real goal and very little focus. Examples include flipping through a magazine and 'channel-surfing'.

Searching

Passive attention: This entails activities such as listening to the radio or watching television programmes, where there may be no information-seeking intended, but where information acquisition may take place.

Passive search: It signifies those occasions when one type of search (or other behavior) results in the acquisition of information that happens to be relevant to the individual.

Active search: It is the type of search most commonly thought of in the information science literature, where an individual actively seeks out information.

Web activities	Desires+	Intentions*
Directed browsing	High level of eagerness	Short-term goal orientation
Semi directed browsing	Medium level of eagerness	Persistent, predictive
Undirected browsing	Little or no eagerness	Casual objective
Undirected viewing	Knowledge broadening	Coarse knowledge gain
Conditioned viewing	Targeted aims and objectives	Specialization
Informal search	Restrictive Knowledge attainment	Limited attempt
Formal search	Unbounded Knowledge attainment	Sincere attempt
+Desires attribute means the desire to attain an anticipated level of information		
*Intentions attribute means the purpose of gaining specific information		

Table 1: Psychological Characteristics

Ongoing search: Where active searching has already established the basic framework of ideas, beliefs, values, or whatever, but where occasional continuing search is carried out to update or expand one's framework.

Viewing

Viewing can be used to describe a pattern of micro-moves of the individuals. The viewing classification is explained as follows:

Undirected viewing: In this type, the individual is exposed to information with no specific informational need in mind. The overall purpose is to scan broadly in order to detect signals of interest. Many and varied sources of information are used, and large amounts of information are screened. The granularity of information is coarse, but large chunks of information are quickly dropped from attention. The goal of broad scanning requires the use of a large number of different sources and different types of sources.

Conditioned viewing: Here the individual directs viewing to information about selected topics or to certain types of information. The overall purpose is to evaluate the significance of the information encountered in order to assess the general nature of the impact on the organization.

Informal search: During this search, the individual actively looks for information to deepen the knowledge and understanding of a specific issue. It is informal and involves a relatively limited and unstructured effort. The overall purpose is to gather information to elaborate an issue to determine the need for action by the organization.

Formal search: In this search type the individual makes a deliberate or planned effort to obtain specific information or types of information about a particular issue. Search is formal because it is structured according to some pre-established procedure or methodology. The granularity of information is fine, as search is relatively focused to find detailed information. The overall purpose is to systematically retrieve information relevant to an issue in order to provide a basis for developing a decision or course of action [12].

4.3 Browsing activities and Conative Attributes

Each web activity inherits a relation with the psychological element of every individual. The conative attributes are more easily recognized as compared to the affective behavior. Later in this paper, we will confront an argument on how we can appreciate affective behavior in web setting. Table 1discusses these psychological characteristics.

Web Data Acquisition

The usage data collected at the different sources represents the navigation patterns of different segments of the overall Web traffic, ranging from single-user, single-site browsing behavior to multi-user, multi-site access patterns.

Server Level Collection: A Web server log is an important source for performing Web Usage Mining because it explicitly records the browsing behavior of site visitors. The data recorded in server logs reflects the (possibly concurrent) access of a Web site by multiple users. These log files can be stored in various formats such as Common log or Extended log formats. Packet sniffing technology is an alternative method to collecting usage data through server logs. Packet sniffers monitor network traffic coming to a Web server and extract usage data directly from TCP/IP packets. The Web server can also store other kinds of usage information such as cookies and query data in separate logs. Cookies are tokens generated by the Web server for individual client browsers in order to automatically track the site visitors.

Client Level Collection: Client-side data collection can be implemented by using a remote agent (such as Java scripts or Java applets) or by modifying the source code of an existing browser (such as Mosaic or Mozilla) to enhance its data collection capabilities. The implementation of client-side data collection methods requires user cooperation, either in enabling the functionality of the Java scripts and Java applets, or to voluntarily use the modified browser. Client-side collection has an advantage over server-side collection because it ameliorates both the caching and session identification problems.

Proxy Level Collection: A Web proxy acts as an intermediate level of caching between client browsers and Web servers. Proxy caching can be used to reduce the loading time of a Web page experienced by users as well as the network traffic load at the server and client sides. The performance of proxy caches depends on their ability to predict future page requests correctly. Proxy traces may reveal the actual HTTP requests from multiple clients to multiple Web servers. This may serve as a data source for characterizing the browsing behavior of a group of anonymous users sharing a common proxy server.

Data Abstractions

The information provided by the data sources described above can all be used to construct/identify several data abstractions, notably users, server sessions, episodes, click-streams, and page views. In order to provide some consistency in the way these terms are defined, the W3C Web Characterization Activity (WCA) has published a draft of Web term definitions relevant to analyzing Web usage. A user is defined as a single individual that is accessing file from one or more Web servers through a browser. While this definition seems trivial, in practice it is very difficult to uniquely and repeatedly identify users. A user may access the Web through different machines, or use more than one

Field Data type	Example
Time (Unix system format)	814679050
Machine name: process id	Dp: 485
User id	204
Window number	1
Event/action path	Menu/File/Open/URL
Same/new window	Same…Window
Final action	Open…URL
URL of page navigated to or URL modified	http://www.testfun.com/~games/
Filename or email address	GI96/info.html
Title of page navigated to	Introduction to TestFun

Table 2: Log Entry fields with examples.

agents on a single machine. A page view consists of every file that contributes to the display on a user's browser at one time. Page views are usually associated with a single user action (such as a mouse-click) and can consist of several files such as frames, graphics, and scripts. The aggregate page view is of importance when discussing and analyzing user behavior.

A click-stream is a sequential series of page view requests. Again, the data available from the server side does not always provide enough information to reconstruct the full click-stream for a site. Any page view accessed through a client or proxy-level cache will not be visible from the server side. A user session is the click-stream of page views for a singe user across the entire Web. Typically, only the portion of each user session that is accessing a specific site can be used for analysis, since access information is not publicly available from the vast majority of Web servers. The set of page-views in a user session for a particular Web site is referred to as a server session (also commonly referred to as a visit). A set of server sessions is the necessary input for any Web Usage analysis or data mining tool [13]. Table 2 [14] is an example of log file and its field values.

4.4 User Sessions and Affective attributes

The frequency of events taking place during a user interaction is very significant for their behavioral analysis. The data evolved from these interactions are analyzed to determine the relationship between certain mental attribute and its corresponding response time. Some of the affective attributes like Excitement, Nervousness and Patience call for further investigation in this area.

Response time data

Both site response times and a user response time provide clues to many aspects of user attributes. Log files supply a source of observations of such response times. Slow site response can indicate an overly large file. If transfer of this file is commonly interrupted (recorded in the log file as an error), then you can ascertain that visitors are not patient enough to view the file. In contrast, a web page that has a high average ‘user response time’ (viewing time) very likely has content of great interest. It could result into a digital expression of excitement or nervousness. A history list is maintained to keep a track of the recency and frequency of page visit. Illustrations of these activities are provided in Table 3.

Analysis Approach

Mean Times: Analyzing user response time data by calculating mean, or average times can create misleading results. Real observational response times include a small fraction of extremely long delays whose causes are not related to the usability of the site. For example, some users go to coffee or talk to their peers between one page reference and the next. This behavior inflates the mean time. The amount of inflation is highly variable simply due to random sampling effects. Together, the inflation and its extreme random variation—even in reasonably large total sets of observations—make mean response times less than reliable for measuring usability-related issues.

Median Times: A more effective approach to analyzing user response times is to use median times. The median is unaffected by the presence of a small fraction of large values. Measurements of medians are much less subject to variability than those of means.

Percentiles Values: In some circumstances, a percentile other than the median is preferable. For example, suppose you are interested in the behavior of regular users but you don’t have user login data or cookie files for determining regular users. As an alternative, you can use the 10th percentile or some other percentile that is likely to represent the faster users, who are most likely to include those most familiar with the site. For example, we can consider a case of visit durations to a transactional web page; the duration for the 10th percentile of visitors (40 visitors) who spent the least amount of time on the page can be calculated as 1.5 minutes [15].

5. MASS CUSTOMIZATION

The above methods are used to aggregate data gathered from the website. The web learners are characterized as individual subjects. The most important task is to group similar subjects together to achieve mass customization. Web learning organizations look for methodologies, which reduce their job of teaching learners on individual basis. This can accomplished using Pattern Discovery.

5.1 Pattern Discovery

Pattern discovery draws upon methods and algorithms developed from several fields such as statistics, data mining, machine learning and pattern recognition. Methods developed from other fields must take into consideration the different kinds of data abstractions and prior knowledge available for Web Mining. For example, in association rule discovery, the notion of a transaction for market-basket analysis does not take into consideration the order in which items are selected. However, in Web Usage Mining, a server session is an ordered sequence of pages requested by a user. Detailed discussion on any of the patterns discovery analysis is beyond the scope of this paper.

Statistical Analysis

Statistical techniques are the most common method to extract knowledge about visitors to a Web site. By analyzing the session file, one can perform different kinds of descriptive statistical analyses (frequency, mean, median, etc.) on variables such as page views, viewing time and length of a navigational path. Many Web traffic analysis tools produce a periodic report containing statistical information such as the most frequently accessed pages, average view time of a page or average length of a path through a site.

VISIT NO.	URL	ACTION
16	acsl.cs.uicu.edu/kaplan/applets	Open URL
15	acsl.cs.uicu.edu/kaplan/work-environ	Open URL
14	acsl.cs.uicu.edu/kaplan/worlds	Open hotlist
13	www.acm.org/sigchi/chi96/forms/Pro	Open URL
12	www.acm.org/sigchi/chi96/call/index	Open URL
11	www.acm.org/sigchi/chi96/	Open URL
10	www.acm.org/sigchi/homepage	StartUp Doc.
9	www.acm.org/sigchi/homepage	Back
8	www.acm.org/sigchi/cscw96/	Back
7	www.acm.org/sigchi/cscw96/dates	Open URL
6	www.acm.org/sigchi/cscw96/	Open URL
5	www.acm.org/sigchi/homepage	Back
4	www.acm.org/sigchi/chi96/	Back
3	www.acm.org/sigchi/chi96/Deadlines	Open URL
2	www.acm.org/sigchi/chi96/	Open URL
1	www.acm.org/sigchi/homepage	StartUp Doc.

(a) A trace of the last 16 pages visited, and the user actions to get them. The top page (16) was just visited and the rest are in order of visit.

(a) Sequential ordering by recency	16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1
(b) Recency, duplicates in latest position	16, 15, 14, 13, 12, 11, 10, 8, 7, 3
(c) Recency, duplicates in original position	16, 15, 14, 13, 12, 7, 6, 3, 2, 1
(d) Frequency, second key recency	10, 11, 8, 16, 15, 14, 13, 12, 7, 3
(e) Stack, sessional	16, 15, 14, 13, 12, 11, 10
(f) Stack, persistent	16, 15, 14, 13, 12, 11, 10, 1
(g) Context-sensitive web	14 (16, 15) 10 (13, 12, 11, 8, 7, 3)
(h) Hyperlink sub-list sub-space (Session 1 only)	16 12 (13) 7 15 (16) 11 (12, 3) 3 14 (15) 10 (11, 6) 13 8 (7)

(b) Examples of history lists conditioned by different methods and numbers represent the URLs visited.

Table 3: Example of Digital Gesture

Association Rules

Association rule generation can be used to relate pages that are most often referenced together in a single server session. In the context of Web Usage Mining, association rules refer to sets of pages that are accessed together with a support value exceeding some specified threshold. These pages may not be directly connected to one another via hyperlinks. The association rules may also serve as a heuristic for prefetching documents in order to reduce user-perceived latency when loading a page from a remote site.

Classification

Classification is the task of mapping a data item into one of several predefined classes [16]. In the Web domain, one is interested in developing a profile of users belonging to a particular class or category. This requires extraction and selection of features that best describe the properties of a given class or category. Classification can be done by using supervised inductive learning algorithms such as decision tree classifiers, naive Bayesian classifiers, and k-nearest neighbor classifiers, Support Vector Machines etc.

Sequential Patterns

The technique of sequential pattern discovery attempts to find inter-session patterns such that the presence of a set of items is followed by another item in a time-ordered set of sessions or episodes. By using this approach, analysts can predict future visit patterns, which will be helpful in placing advertisements aimed at certain user groups. Other types of temporal analysis that can be performed on sequential patterns include trend analysis, change point detection, or similarity analysis.

Dependency Modeling

Dependency modeling is another useful pattern discovery task in Web Mining. Several probabilistic learning techniques can be employed to model the browsing behavior of users. Such techniques include Hidden Markov Models and Bayesian Belief Networks. Modeling of Web usage patterns will not only provide a theoretical framework for analyzing the behavior of users but is potentially useful for predicting future Web resource consumption [13].

5.2 Clustering

Our only source of information is web log data that records users' document access behavior. We wish to use this information to construct clusters that represent closely related documents where the relevant information cannot be observed by simply examining the documents themselves. One requirement is that we must not predetermine the number of clusters and that we must use as little initial information as possible.

In the Web Usage domain, there are two kinds of interesting clusters to be discovered: usage clusters and page clusters. Clustering of users tends to establish groups of users exhibiting similar browsing patterns. Such knowledge is especially useful for recognition of identical learners psychological state.

One can use clustering techniques to impose an organizational structure on a collection of web usage data by clustering together groups that are related or similar based on their content. The clustering induces the number and type of categories from the data. The organizational structure is data-driven and you don't have to prespecify document categories. Many clustering techniques produce flat organizational structures in which document groups are disjoint. Other clustering techniques produce hierarchical structures in which groups may be decomposed recursively into subgroups corresponding to refined categories. In any case, clustering turns unstructured document collections into organized groups that provide a summary view of the documents in that group. Figure 2 refers to the visualization of clustering. A short introduction to two of the vastly used clustering methods is given below:

K-means Clustering: K-means constructs a partition of a database of n objects into a set of k clusters where k is an input parameter. Each cluster is represented by the center of gravity of the cluster (k-means) or by one of the objects of the cluster located near its center and each object is assigned to the cluster with its representative closest to the considered object. Typically, this algorithm starts with an initial dense partition of database and then uses an iterative control strategy to optimize the clustering quality. However,

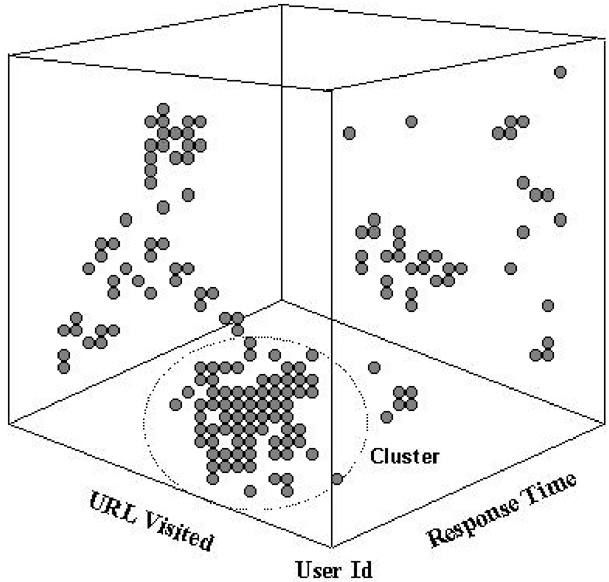

Figure 2: Interactive 3-D environment for visualizing Clustering.

K-means requires that the user provide the number K of clusters as initial input.

Hierarchical Agglomerative Clustering (HAC): HAC creates a hierarchical decomposition of a database. The hierarchical decomposition is represented by a dendrogram, a tree that iteratively splits database into smaller subsets to consist only one object. In such a hierarchy, each level of the tree represents a clustering of database. It works as follows. Initially, each object is placed in a unique cluster. For each pair of clusters, some value of dissimilarity or distance is computed. In every step, the clusters with the minimum distance in the current clustering are merged until all points are contained in one cluster.

6. FUTURE WORK

This area of web learning demands a lot of reckoning. Vast and in-depth empirical analysis is required for classification of conative and affective behavior. We also have to consider the possibility of multiple learners sharing a single sessions which makes this behavioral recognition perplexed. This understanding is meant for learners when online. In situations when learners are educated offline, we need to create an intelligent environment that identifies the digital gestures of the learners. We may be required to achieve a convergence between learner psychological behavior and their gestures. Drawing conclusions in a short period of time and in situations when few interactions are registered is one intricate job. There may be several instances, which may lead to a crossroad-like situation. A systematic classification mechanism is needed.

7. CONCLUSION

In this paper, we start with the argument about imparting personalized learning in WWW environment. We support this stand by the various research conclusions of past and present. The various activities prevalent in web learning i.e., browsing, searching and viewing which help in deciding the psychological factors are elucidated. The vital correlation between web activities and conative and affective attributes form the crux of the whole discussion. To finish, the mass customization aspect of web learning is presented and can be attained using Pattern Discovery and Clustering.

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