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Using User Interaction to Model User Comprehension on the Web Navigation

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***Abstract*: The user behavior and interaction on the web have evolved from the use of static information resources to the use of dynamic and interactive applications. This is why it is necessary to extend the current studies of user web navigation behavior to improve the quality of web services. In this work, a computational cognitive model of web navigation is proposed. The model is based on the principle that users interact with the interface, in order to decode and interpret the message, and gradually unfolds from it all the meanings encoded by the UI designers. Based on semiotic theories of HCI and web navigation models, the plausibility of the proposed model is discussed. Thus, the model seeks evidence about the user comprehension on the user interaction; using Bayesian nets, it infers user interactive artifacts comprehension and uses this information in order to draw conclusions about interface and task concepts understanding. In the first experiments, we use the model to predict user navigation and we compare predictions with real user interaction.**

Keywords: Web navigation modeling, user behavior modeling, user comprehension.

I. Introduction

One of the main activities people do in the web is the so called web navigation, which involves a mix of actions such as: browsing web pages, using searching engines and browser's tools [15]. In that sense, web navigation study has helped to understand the user´s behavior when they interact with a web site.

Traditionally, modeling of user web navigation behavior is achieved through analysis of web navigation records. This analysis has been useful to learn about user and use this information to model knowledge, interests, goals, background and other individual qualities [4]. Modeling of user traits has been applied to specific areas; for example, identify learners' behaviors and learning styles automatically during training sessions, based on trace analysis [3].

Cognitive models of web navigation try to describe how users analyze and react when navigate in the web. Several attempts to model cognitive processes involved in web navigation such, as CoLiDeS[8], SNIF-ACT [16] and MESA [11], are based on the assessed relevance of screen objects to users' goals. The subsequent works, as CoLiDeS+ [14], complement preceding models considering previous interaction to user's model. These cognitive models of web navigation compute the user action by using information from the hyperlink text alone and ignore all other information on a page. However, studies as [7] have focused on verifying the validity of this hypothesis by investigating the role played by the content in addition to link text on user decisions.

Using empirical data, Meiss et al. [10] characterize several properties of web interaction that cannot be reproduced with traditional web navigation models, and they propose the usage of an agent-based model that adds several realistic browsing behaviors.

Nigan and Jain [13] present a new way for modeling the user web navigation sessions. Structuring user behavior as Dynamic Nested Markov model, their proposal reduces time complexity to predict user interaction.

In this work, we study how user interaction can be used to determine his/her comprehension of a system interface. Additionally, we discuss why user comprehension of interface is relevant to take web navigation decisions. Finally we propose one computational model which determines user's comprehension through the usage of system's interface.

This paper is organized as follows: first, we review some of the research work on web navigation modeling. After, we discuss a semiotic account on Human Computer Interaction (HCI). In addition, we introduce the model of web navigation that we propose and its cognitive grounds. Finally, we validate this model and conclude by explaining some of the implications of this work.

II. Web Navigation Modeling

Information foraging theory describes the human species as hungry for information [15], Pirolli also indicates, that navigating the Web has become a common way to find information needed to solve such everyday problems. In agreement with this idea, when people browse the web for information, they must base navigation decisions on assessments of *information scent* cues associated with interface objects. Traditionally, web navigation models consider only cues related with links from one web page to another. These cues are the small snippets of text and graphics that are associated with Web links. According to these models, users must use these cues presented on the web-pages they currently viewing in order to make navigation decisions. Models that follows this idea, assume that the measure of information scent provides a means to predict how users will evaluate different links on a web-page, and as a consequence, the likelihood that a particular link will be followed.

The computational cognitive model developed by Pirolli and Fu [16], named Scent-based Navigation and Information Foraging in the ACT architecture (SNIF-ACT), simulates users performing web tasks. Their model predicts navigational choices (when following a web-link or when leaving the website) based on the information scent of each page. In this model, information scent is calculated as a mutual relevance between the user's goal and link texts based on word occurrences and co-occurrences in the Internet using an information-theoretic measure known as Pointwise Mutual Information (PMI). The approach of Kitajima et al. [8], known as Comprehension-based Linked model of Deliberate Search (CoLiDeS), measures information scent of a particular web page to the user's goal based on three factors: semantic similarity, frequency and literal matching. Semantic similarity is calculated based on latent semantic analysis (LSA).

However, there are situations in which link labels are not fully descriptive according to user needs or they are not knowledgeable enough to accurately assess the relevance of link descriptions to their goals. The model of Miller and Remington [11], called Method for Evaluating Site Architectures (MESA), is focused on effectiveness of link selection strategies, given various link relevancies and site structures. They do not give an account for how link relevancies are assessed. In contrast, the link relevancies are regarded as inputs to the system. Oostendorp and Juvina [14] propose that the context of a navigation session influence the assessing relevance of a particular page object to the user's goal. Their model (COLIDES+) describes the use of path adequacy, the relevance of a navigation path to the user's goal, beside information scent in web navigation modeling.

Originally SNIF-ACT treats a page as a single information patch. However, its authors indicate that there is not known barrier to extend SNIF-ACT to deal with a page as a collection of regions. Whereas that, CoLiDeS considers each page as a collection of patches and uses information scent to select which particular patch to forage.

In [9] is indicated that information scent can misleads the user, for example, when the user is guided to a patch with high information scent, where there are multiple high-scent links, none of which are on the solution path. Bhavnani et al. [2] have argued background knowledge is also crucial for determining the reliability of the information found, so that misleading information is avoided.

Kitajima et al. indicate that models as CoLiDeS and SNIF-ACT can complement each other and each can benefit from incorporating the specialized strengths of the other. From their point of view, CoLiDeS has focused on individual web pages and its components, and SNIF-ACT has worked at a higher level providing good explanations of navigation from one webpage to another and one website to another.

Their research shows that scanning a webpage to grasp its structure requires the ability to segment the web page into information patches, and they indicate that this process is highly compatible with Information Foraging theory.

III. Semiotic Approach to HCI

Semiotic investigations are focused on understanding how people use signs to communicate [5]. Semiotic Engineering provides a semiotic account of HCI, stressing the fact that designers of interactive software communicate their design vision to users through the user interface [19]. The message is encoded through the signs in the interface (words, icons, graphical layout, sounds, and widgets). As users interact with the system, they discover and interpret this message. The properties and behavior of signs in the interface allow the user to understand what the system does, and how to use the interface.

The interface includes the designer's message about how to use the system, and why. But the messages can be interpreted by users in ways that were not meant by the designer. Some of those misinterpretations will lead users to errors. To facilitate the users' comprehension of interface signs, designers cue the interpretations they expect from users by introducing signs that have the potential to trigger consistent abductions in the users' minds.

Using these cues, user constantly generates and revises meanings for the interface signs. De Souza [19] indicates that m*eaning* is an evolving and unpredictable process, rather than a static abstract end point that we can eventually reach in the process of interpretation. Rather, we generate meanings that are continually 'revised' and 'elaborated' as a result of our encounters with them throughout life.

It is expected that user comprehension will be carried to *right* range of meanings because of user interaction, and this lets user to achieve his/her goals.

IV. Modeling user Comprehension

Following semiotic point of view of HCI, the user comprehension of interface signs determines how user chooses signs in order to achieve his/her goals. Therefore, web navigation decisions depend on user's comprehension of web interface signs. Moreover his/her comprehension can be modified because of his/her interaction with them.

This work is focused on looking for evidences about how users apply his/her interface comprehension to take navigation decisions. In this study, we consider only interactive interface signs, which we call *interactive artifacts*.

A. Representation of designer's message

Considering web sites, the content data in a site or designer's message is the collection of objects and relationships that are conveyed to the user. The data sources used to deliver or generate this message include static HTML pages, multimedia files, dynamically generated page segments from scripts, and collections of records from the operational databases. The message also includes semantic information, that is to say, underlying domain ontology for the site. Domain ontologies may include conceptual hierarchies over page contents, such as product categories, explicit representations of semantic content and relationships.

The structure data represents the designer's view of the content organization within the site. This organization is captured via the inter-page linkage structure among pages, as reflected through hyperlinks. The structure data also includes the intra-page structure of the content within a page. All these elements represent the information structure of the site. The structure can be represented as tree structures over the space of task of the user (figure 1).

Figure 1. Information structure of the site

The hyperlink structure for a site is normally captured by the "site map", usually represented as a directed graph. A site map must have the capability to capture and represent the information-user goal relationships.

Finally, the designer's message includes how to use interactive artifacts to achieve the possible goals. According to Shneidermann and Plaisant [18], the designer can map the objects and actions of the user's world to interface metaphors and actions. In this work, the arrangement of tasks, actions and objects are represented also as tree structures (figure 2).

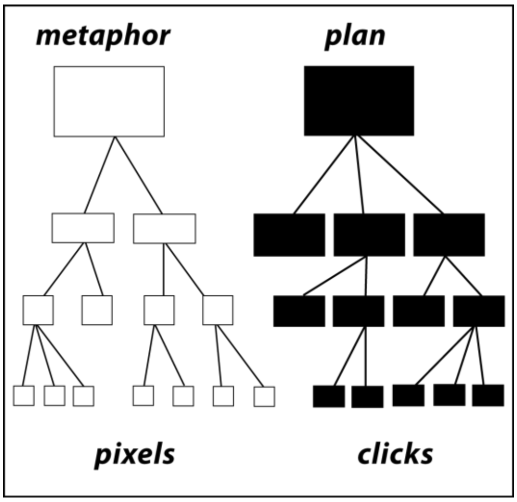

Figure 2. Task and interface objects

B. *Gradually comprehension of user interface*

In agreement with previous ideas, interactive artifacts comprehension will be gradually achieved. Designer chooses the best sign to communicate his/her intent. This representation (the sign) guides the first user interpretation, and the usage of this artifact unfolds from it all the meanings encoded by the designers and produces new user meanings about the interactive artifact in relationship with his/her goal.

In this work is proposed that, for each interactive artifact, its related user-goal is decomposed on four sub-goals: communicate existence, communicate behavior, communicate functionality, and communicate user-goal.

We associate the achievement of these sub-goals with the interactive artifacts comprehension by the following discovery stages: simple discovery, type discovery, functionality discovery, role discovery.

These stages can be achieved at the very moment that user interacts with them. When the user is exploring a web interface and identifies an interactive artifact, then she/he recognizes the possibility to use it (simple discovery). When the user decides to interact with an artifact, he/she must identify which kind of artifact is, and then he/she recognizes how to use it (type discovery). When the user frequently uses an artifact, he/she recognizes what happens (functionality discovery). When the user learns why he/she must interact with the artifact in order to achieve his/her goal, he/she recognizes its task-related role (role discovery).

C. *Predicting discovery stage achievement of an interactive artifact*

No one can predict which is *the exact* meaning a user attributes to any particular interface artifact. Not even statistical methods can be safely used when it manages infinite possibilities of meanings. According to semiotic engineering, user interaction can offer traces of communicability of interfaces signs, and as a result, can offer as well evidence of user comprehension of the original designer's message [19]. We can observe patterns of user interaction and identify achieved stages that can be spotted during interaction.

Web usage mining [12] can supplement the automatic discovery and analysis of patterns in user interactions with web resources on one or more web sites. Web usage mining can help us to capture, model, and analyze traces of user comprehension of interface using user interaction.

Intuitively, analyzing user interaction we identify when was the first interaction with an artifact (simple discovery), when user was able to use it (type discovery), when he/she frequently utilized an artifact during he/she interaction (functional discovery), and when user achieved his/her goal following common behavioral patterns (role discovery).

1) *Analyzing user interaction*

The possibility of apply web usage mining to analyze user behavior implies that we must be able to infer some needs or characteristics about a user based on previous or current interactions with that user, and possibly other users.

The primary data sources used in web usage mining are the server log files, which include web server access logs and application server logs. Additional data sources that are also essential for pattern discovery include the information structure of the site, operational databases, application templates, and domain knowledge. Each entry of log files may include fields identifying the time and date of the request, the IP address of the client, the resource requested, possible parameters used in invoking a web application, status of the request, HTTP method used, the user browser and operating system, the referring web resource, and, if available, client-side cookies which uniquely identify a repeat visitor.

Depending on the purposes of the analysis, this data must be converted at different levels of abstraction. Traditionally, the most basic level of data abstraction is that of a *page view*. Mobasher [12] defines a page view as an aggregate representation of a collection of web objects contributing to the display on a user's browser resulting from a single user action. Following this idea, each page view can be viewed as a ordered set of web objects or resources related to a specific user task, for example, reading an article, viewing a course description, or sending an email.

Considering user behavior, the most common behavioral abstraction is that of a *session*. According to Mobasher [12], a session is a sequence of actions by a single user during a single visit. In the simplest version, a session can be associated to a subset of page views in the session that are significant or relevant for the analyzed tasks. Each session can be used directly to generate the user profile. However, if the purpose of analysis is to capture the behavior of users over time (i.e., over multiple sessions), all sessions corresponding to a user can be combined and aggregated to construct the profile for that user.

Starting of designer's description, we assumes that each page is composed of interactive artifacts on the screen (figure 3) — action graphic, iconic link, hypertext link, for example.

Figure 3. Interactive artifacts of a page.

As shown in table 1, each usage of interactive artifacts is registered in web server logs.

Host	Source	Artifact
189.144.19.98	/personal.jsp	personal button
189.144.19.98	/academic.jsp	Academic button
132.248.36.33	/personal.jsp	personal button

Table 1. Register of user interaction.

2) Inferring artifact comprehension

We analyze usage of interactive artifacts to study how users navigate through the web interface. Table 2 shows user interaction as a sequence of used artifacts. Applying data-mining techniques to analyze this sequences we can obtain clusters that describe the usage of artifacts. In these clusters we can identify how users interact with artifacts in order to resolve his/her task, and then we look for evidence of user comprehension of interactive artifacts.

Host	Navigation path	Date
189.144.19.98	[a288,a11,a21]	2009-03-11 12:05:25
189.130.18.39	[a288,a33,a33,a11,a3]	2009-03-13 09:02:51
132.248.36.33	[a288,a11,a21]	2009-03-11 00:35:09

Table 2. User Navigation Path.

With the purpose of illustrate this idea; we apply the analysis of usage of interactive artifacts to a web site dedicated to the registration of interested students to apply for one scholarship. The complete web application covers several tasks, for this study we focus on one task: *student fulfill the registration form*.

The registration form is composed by the interactive artifacts listed in table 3. For simplicity we code artifacts with single symbols. Table 3 includes interactive artifacts, his action, and code.

Artifact	Action	Code
login button	Login	a_0
home link	Go to home	a_1
personal button	Go to personal information	a_2
academic button	Go to academic information	a_3
activities button	Go to activities information	a_4
additional button	Go to additional information	a_5
logout link	Logout	a_6
save button	Save data	a_7
next button	Continue	a_8
text fields	Fill data	a_9
confirm button	Confirm information	a_{10}
correction button	Back to modify information	a_{11}

Table 3. Interactive artifacts of registration form.

Each session is identified by its host and it includes the sequence of actions done along this session. We use a data set of 5180 user's sessions, composed of host data, date of session and a sequence of used artifacts as shown in table 2.

To understand the usage of this application, we look for clusters of sequence of user actions using Weka [6] data mining tool. The Weka workbench is a collection of machine learning algorithms and data preprocessing tools. It provides support for the whole process of experimental data mining, as well as preparing the input data, evaluating learning schemes statistically, and visualizing the input data and the result of learning [20].

With this analysis, we can identify the following centroids associated to detected clusters:

1. **[a_0 a_0]** – User fails login.
2. **[a_0 a_1 a_6]** – User tests username and password.
3. **[a_0 a_1 a_2 a_3 a_6]** – User browses the web application freely.
4. **[a_0 a_1 a_8 a_8 a_6]** – User browses the web application following instructions.
5. **[a_0 a_1 a_8 a_9 a_7 a_{11} a_9 a_7 a_{11} a_9 a_7 a_{11}]** – User corrects frequently his information.
6. **[a_0 a_1 a_9 a_7 a_{10} a_6]** – User captures specific information in one section.
7. **[a_0 a_1 a_9 a_8 a_2 a_9 a_8 a_3 a_9 a_8 a_7 a_{10} a_6]** – User fills complete data information.
8. **[a_2 a_9 a_7 a_{10} a_6]** – User browses web application using web navigator controls.

These centroids represent some typical global behaviors of users, which are intuitively described by web designers of this web application.

In [20], it is indicated that if a clustering method were used to label the instances of the training set with cluster numbers, that labeled set could then be used to train a rule or decision tree learner. The result forms an explicit description of the classes.

Using the previous clustering, we train a classifier based on a Bayesian network. The complete data set is divided into: training data set, testing data set and cross validation data set. In training, testing and cross validation stage, the classifier reaches 96%, 93% and 92% of instances correctly classified, respectively.

This resulting Bayesian network described the global behavior of user in terms of his interaction. This kind of Bayesian network can be used to infer the next action considering past actions.

We can apply the same process to obtain specific patterns of usage for each specific task, i.e. save data, considering only related interactive artifacts. The corresponding specific clusters are less intuitive than global clusters, but they capture specific behavior of user to fulfill a task.

Using this kind of clusters we can train an explicit Bayesian network for each u_i user, linked to the comprehension of each interactive artifact.

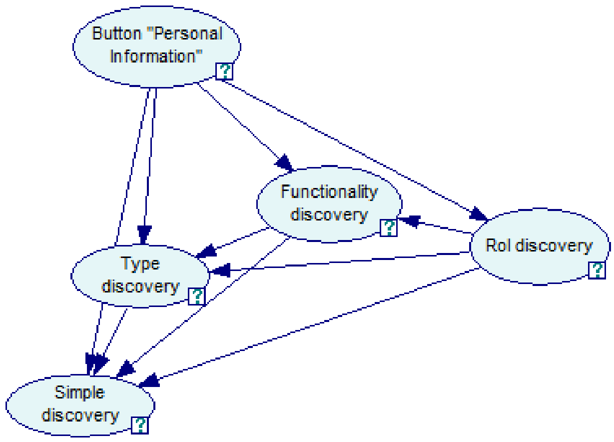

Figure 4. Bayesian network for a specific interactive artifact comprehension

This $b_{i\text{-}j}$ Bayesian network can represent the specific experience of u_i with the a_j interactive artifact. In accordance with this, figure 5 shows the starting point of the Bayesian network.

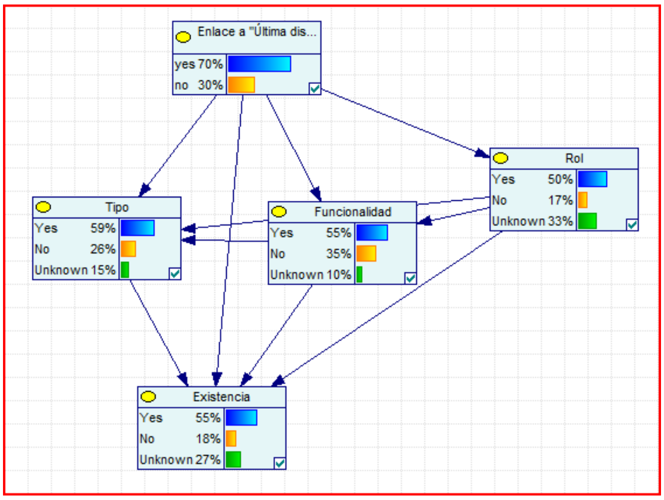

Figure 5. Starting point of the Bayesian network

When user starts a new session, this Bayesian network contains the information of his/her previous interaction. Then each new interaction produces new evidence that is reflected in over the Bayesian network (figure 6).

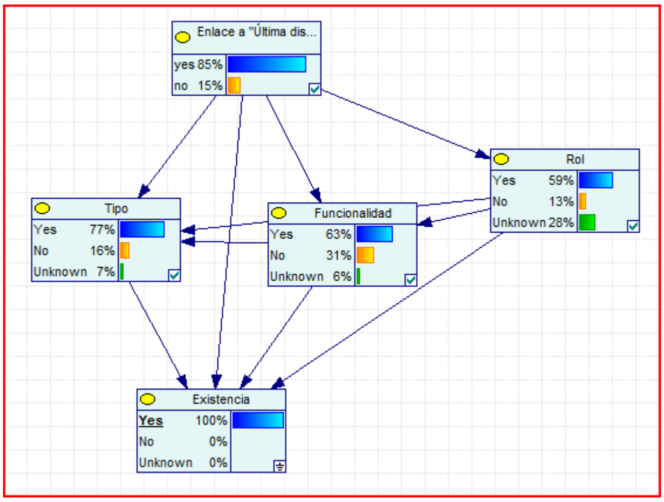

Figure 6. Updating evidence over the Bayesian network

D. A Spreading Activation Model of User Comprehension

Pirolli [15] have pointed out that a model focused on understanding and predicting the web navigation, needs to take into consideration how those structures of information are perceived by people, since the way they perceive the information will determine the way in which they will react when trying to reach their goals. In web navigation, the main structure is the information architecture of the site. This structure will be understood trough user interaction.

Considering discovery stages, the achieving of each one of these stages can modify user comprehension about the system. Then the reach of each stage spreads some activation signal over the information architecture. We expected that this model of activation help us to draw user comprehension about interactive systems.

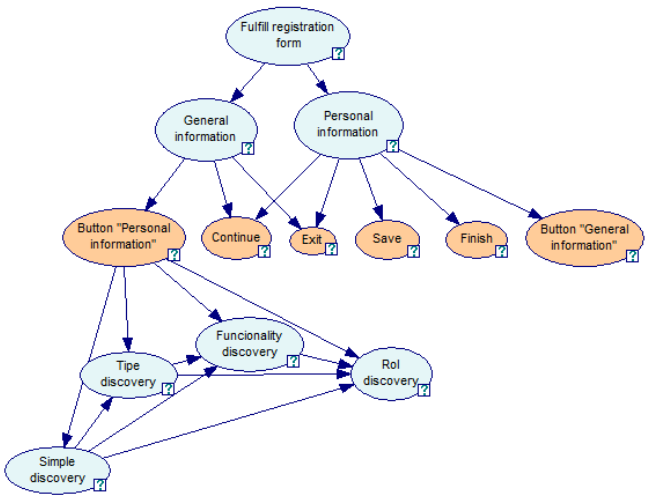

Figure 7. Spreading activation network of user comprehension

E. Prediction of user interaction based on rational analysis

Information foraging theorists have used ACT-R spreading activation models of information scent to produce consistent representations of how people navigate the Web by following an information scent trail. They have used mathematical models from rational analyses to calculate and compare utility values and accurately describe how people decide which particular information patch to forage, when to select links to move to another webpage, when to back up to a previously visited information patch, and when to discard a website and search for a new and optimistically better information patch.

The rational analysis of the use of information considers that the goal of the user is to use proximal external information scent cues (e.g., a web-link) to predict the utility of distal sources of content (i.e., the web-page associated with a web link), and to choose to navigate the links having the maximum expected utility [17].

In this work, the expected utility is related with user experience with the interface. This information is contented in the Bayesian model.

V. Evaluation

Pirolli et al. [17] develop a method aimed at extracting and validating cognitive models against an individual user. The methodology involves creating a user trace: a record of all significant states and events in the user interaction based on the analysis of eye tracking data, application logs, and think-aloud protocols. They use their user-tracing architecture for developing simulation models of user interaction and for comparing simulation models against user-trace data. The simulation model is given the same tasks as observed users, and then the model simulates activity with the web to achieve those tasks. The user tracing architecture compares each action of the simulation directly against observed user actions.

Following these ideas, the components of our user tracing architecture are:

1. Task. Hierarchical description of web site task.
2. Instrumentation. User interaction extracted from log files.
3. Cognitive-perceptual simulation model based on user comprehension.
4. User Comparator. The model is run in the user trace architecture. On each cycle, the model makes a prediction, generating another element in the user interaction sequence. The user trace comparator uses a set of rules to determine whether there is a match with the real user interaction; if not, an error is scored against the model and it is set back on track.

Our experiments begin with the designing of *ecologically valid tasks* [17], that is, tasks that people do in real situations. The real scenario selected for this work was *Moodle system*. 20 users used our moodle system along 16 weeks; we collect the corresponding usage data and analyze this data in order to reconstruct their interaction.

A. Tasks

All valid tasks are described as a hierarchical relation between tasks, subtasks and interactive artifacts (figure 8). For each valid task are indicated all needed subtask as a means to do this valid task. At the end, for each valid subtask is indicated all required interactive artifacts to subtask has done.

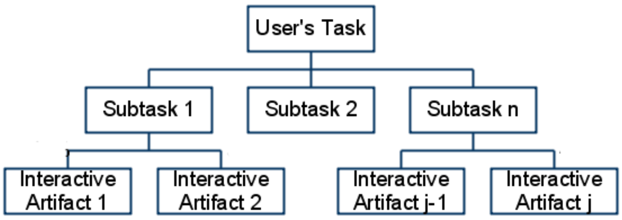

Figure 8. Task decompositions

At the 13th week, users must be done the following task:

13th week task: For the subject of this week, you must review the subject using the document published in the platform, participate on corresponding discussion forum and resolve the associated exam.

Figure 9 presents hierarchical representation for 13th week task.

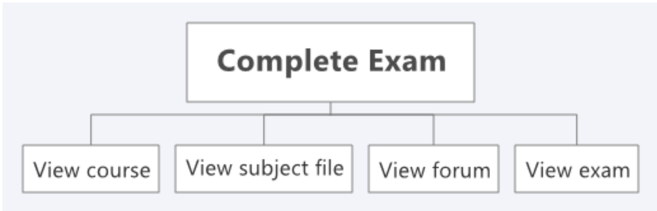

Figure 9. Hierarchical representation for 13th week task

Users were encouraged to perform this task as they would do typically, and we observe their behavior using web log files.

In our evaluation we consider four tasks that users perform. The first two are similar, the third excludes the view forum, and for the last task, users carried out the assignment as they would typically, but they were also instructed to think out loud as they performed their task.

B. Instrumentation

For these experiments, we capture user interaction in web server log files. As mentioned before, each usage of interactive artifacts is registered in web application logs. This information indicates how users navigate through the web interface. It is used to identify how users interact with artifacts in order to resolve his/her task, and then representation of comprehension stage for each user.

Using this information we develop a Bayesian analysis of the expected relevance of each stage on the user comprehension of an interactive artifact.

C. Comparing user behavior with prediction

According to interface designer point of view, the 13th week task must be performed as shown in figure 10. In our observations none followed this sequence of interaction. The most common navigation path is shown in figure 11.

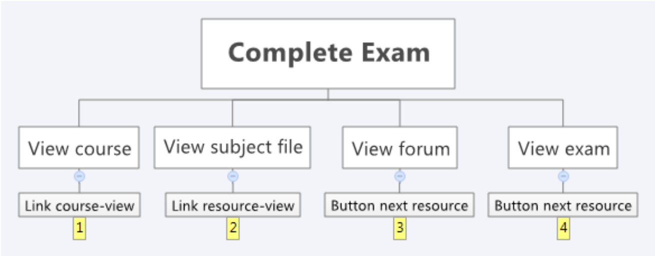

Figure 10. Interface designer point of view

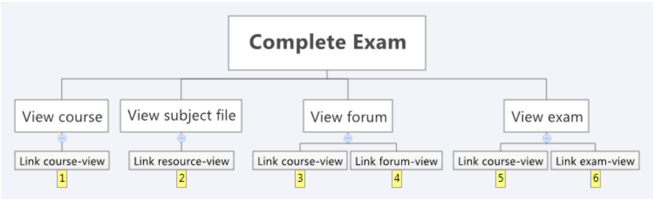

Figure 11. Common navigation path to perform the task

VI. Results and Comments

Our solution decomposed this problem into three parts: (1) a Bayesian analysis of the expected relevance of a artifact on the available task; (2) a mapping of this Bayesian model of user interaction onto a mathematical formulation of spreading activation of user comprehension; and (3) a model of rational choice that uses spreading activation [1] to evaluate the utility of alternative choices of interactive artifacts.

First experiments indicate the plausibility of look for evidence of user comprehension about the interface on user interaction.

The proposed model was able to predict user interaction on some simple navigation tasks.

The several cognitive models of web navigation can complement each other and each can benefit from incorporating the specialized strengths of the other. Our proposal describes another perspective to complement information foraging models.

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