

Reducing Cognitive Load

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Abstract

This paper explores issues related to cognitive load in the contexts of learning, information filtering, user modeling, categorization and personal information organizing behavior. We incorporate expertise from the fields of information science, educational psychology and computer science to report research that can ultimately influence the design of personalized adaptive systems.

1. Introduction

In this paper, we address issues of cognitive load and information filtering. Specifically, we explain how recent research on personalized information filtering can contribute to effective ways to reduce cognitive overload. An examination of this research can be foundational in the creation of computer-based applications tailored to an individual's information needs. We begin with a description of the construct, cognitive load, from an educational psychology perspective and then we examine research in learning, user modeling, information filtering and information organizing behavior.

2. Cognitive load

The concept of cognitive load is a useful construct for cognitive psychologists, educators and designers. From this perspective, cognitive load has usually been conceptualized as the extent to which cognitive resources are taken up by activities

that facilitate learning [14; 48]. In this paper we describe some of the issues that contribute to the reduction of cognitive load as they apply to the areas of learning, user modeling, information filtering, as well as information organizing behavior.

2.1 Learning

A key emphasis of this research involves uncovering aspects of instructional designs (like physically separate text and diagrams) that can contribute detrimentally to cognitive load. For example, early research from this perspective indicated that illustrations and text should be presented in proximity rather than separately. Chandler and Sweller [14; 48] argued that cognitive resources can unnecessarily be overloaded by integrating material from one location with material from another (i.e., “split attention effects”), or by processing material that is overly repetitive (“redundancy effects”).

Mayer [33] summarized a series of principles for effective multimedia design that emerged from his research. These principles relate directly to methods of reducing overload. For example, he argued that unnecessary information or auditory input is detrimental for learning. Additionally, he advocated for limited chunks of text-with-illustrations for initial learning. Research-based principles such as these can inform instructional design and further research in instructional contexts.

2.2. User Modeling and Information filtering

One of the consequences of the Internet is that anyone with access can become an author and a publisher. As a result, the quality of the information is diverse and the quantity of information is daunting [27]. Cognitive load increases with the amount of information to process. This problem is not new but it is certainly aggravated with the advent of computerization, and more recently, the Internet. With this explosion of resources, obtaining appropriate information becomes more important than its availability. In addition, information that is salient for one individual may have little meaning for many others [10]. The need for tools to help users filter streams of information increases as information becomes available in sources such as the WWW.

Personalized information systems such as recommenders, alerting services, and selective dissemination of information are collectively called information filtering systems. A goal of information filtering (IF) is to reduce information overload. IF implies selecting things from a larger set of possibilities and presenting them in prioritized order [31]. Ram [42] defines IF as a system that determines the relevance of a text, based on the relationship between the user's interests and the text's content.

The conceptual framework for the design of an IF system is found in user modeling research. A user model can be described as a system knowledge source containing assumptions on aspects of the user that guide the behavior of the system. A goal of building a user model is to reduce the user's information load. This can be accomplished by adapting either the representation of the task or the task itself. Campbell [11] reviewed several research areas and classified the treatment of information overload as: (1) primarily a psychological experience, (2) an

interaction between task and the persons' characteristics, and (3) a function of objective task characteristics.

The most distinctive characteristic of an IF system is the existence of a profile that models the user's information needs. Belkin and Croft [8] define IF as the process of determining which object in the information stream has the best chance of fitting the user's profile. Shapira and colleagues [46] state that IF is based on modeling the user and presenting the information needs as a profile. Oard and Marchionini [36] view IF as an application of user modeling techniques for information seeking.

2.2.1 User Profiles. The goal of personalization in information delivery is to present information to users to match their information preferences. Profiles, the representations of these information preferences, are the basis for the design of personalized information systems. User profiles are types of user models, [19]. Allen [2] asserts that user models save time while Maes [29] claims they can reduce information overload. According to Borgman and Plute [9] there is not a unique definition of a user model. They depend on the system, the user, and the task being performed. Characteristics and context of the user could be considered when designing interfaces for interactive IR systems. Some of these characteristics are user background, habits, topics of interests, and user status [16]. Allen [2] notes that while the term user model emphasizes information about the person's background, the primary contributors to the model are the "situational task" and the "environmental information"

2.2.2 Profile content. The accuracy of a profile is critical for the performance of any filtering mechanism. Contents of the profile play a major role in the profile's accuracy. User profiles include items such as domain expertise, life style and use of recommended

items. For example, Ardissono and Goy [1] created user profiles for potential customers of electronic shops. The contents of the user profiles led the system to decide which product to recommend, how to present the product descriptions, and how much technical information to include. Petrelli and colleagues [37] tested categorizing visitors to museums according to “classical” dimensions such as age, profession, education, and specific knowledge or background. They also considered situational dimensions such as available time for the visit as well as motivation for the visit. All of this information was used to set system features such as language style and how much content to include.

2.2.3. Empirical evaluations. Filtering systems frequently rely on topics for modeling user interest. Fidel and Crandall [18] performed an empirical study evaluating filtering performance in order to identify attributes that should be included in filtering profiles. They examined criteria users employed to determine whether or not a document was relevant. Although profiles in their filtering system were based on topics, they found that users employed many criteria beyond topics. These results were supported by previous studies in information retrieval [45] where several non-topical criteria were identified. Fidel and Crandall [18] identified thirteen criteria for relevance and fourteen for non-relevance assessments. Some of the criteria for relevance of a document were directly related to the working status and to the product or service of the company. A few other criteria depended on the situation of the individual; that is, whether it confirms one’s beliefs and keeps one updated. On the other hand, when the participants judged a document to be non-relevant, they gave reasons in terms of generality, technicality, familiarity and availability. In order to improve filtering performance, Fidel and

Crandall [18] recommend developing methods to create and maintain useful profiles, incorporating topical and situational criteria into the profiles. Also consistent with previous work were the findings reported by Quiroga and Mostafa [41]. Their results showed how context influenced user-relevance judgments. Their findings provided an explanation for the low performance of filtering systems when profiles are based solely on topics and fail to consider context and characteristics of users. They found five categories of user’s characteristics that influenced feedback assessments: These are: 1) demographic data (age, gender, population/community, marital status); 2) domain expertise (profession / occupation, education, projects); 3) lifestyle (hobbies, habits, work and home environment); 4) health status (illness, intolerance, propensities, disabilities), and 5) health concerns of friends and relatives. Topical characteristics of documents that influenced relevance include orientations (surgical procedure, genetics aspects, side effect), specificity (kind of allergy or exercise); non-topical factors included credibility of the information source, comprehensibility, novelty, format, target audience, availability, title appeal, being a current affair. In order to reduce information and cognitive overload this type of contextual information must be represented in IF systems.

2.2.4. Agents. Agents are software programs that implement the users' perceived goals [21]. One of their applications is acting on behalf of the user, delivering selected, prioritized information [20]. Maes [29] considers information filtering to be one of the many applications facilitated by agents collaborating with their clients in order to alleviate information overload. An advantage of agents is that they facilitate the modeling of users with different domain knowledge. This fact is exemplified in Personalized Text,

a software system that customizes hypertext for the user. Kay and Kummerfeld [23] note that learners should benefit from a personalized hypertext whose structure matches their preferences, interests, goals, and background since people differ in how they best process information.

2.3. Information Organizing Behavior

As the field of human-computer interaction (HCI) becomes concerned with human organization of complex material, importance is given to studies of how humans organize and remember information. Understanding depends on the extent that retrieved information fits the users' schema or ways of knowing. If the new knowledge conforms to the users' previous knowledge, it can be incorporated into their knowledge base. If it does not, the new information is misunderstood or lost. Bartlett [7] proposed a model, which has yet to be refuted, where information is filtered and modified by one's existing schema. Missing information is inferred by our schema to fit our understanding. Schemata models have been used to explain HCI performance in applications such as command languages [49], interpretation of data models [35] programming [5], and learning to program [32]. Analyzing activities associated with problem solving is another way for HCI researchers to focus on complex cognitive processes such as concept formation and categorization [34;15].

2.3.1. Categorization. Categories are the basis for representing information profiles and documents in most IF systems. A better understanding of categorization theories is an essential component to the design of filtering mechanisms that can reduce cognitive overload. Maintaining filtered and relevant information relies in categorization tasks: creating categories of their information needs,

creating categories of published information, classifying, sorting, filing and prioritizing and sharing information. Bowman [10] describes categorizing and organizing as the process of deciding how to relate information and how to determine where it belongs in a hierarchy.

It is worthwhile to note how theories of categorization have advanced toward a user-centered approach. Theories of categorization have evolved from classical, to prototype, to contextual. Each step in this process gets closer to a cognitive approach where building categories includes not only attributes of the object to be classified but characteristics of the human being who is performing the classification task [25].

According to the classical categorization theory, items are grouped on the basis of the characteristics they have in common [47]. This theory was the framework for most of the early research in categorization. Some aspects of the classical theory were especially controversial. Eleanor Rosch's [43] research on prototypes argues against one implication of classical theory: all members in a class are equally representative of the class. Her research collected empirical evidence showing that there are members that are better examples, prototypes or cognitive reference points for a category. For example, robins are judged as more representative of the category bird than penguins.

Another source of problems comes from assigning one exclusive class to each document. This procedure conflicts with principles of categorization that are considered universals. Topics are not exclusive Aristotelian categories, but what Lakoff [25] calls radial, where the category has a predictable center and the non-central members can't be predicted from the central members. Not all the members are equally representative of the class. Boundaries are not deterministically marked, but distance to the center measures how well an item represents its class. It is the task of classifiers to decide

which prototype an interdisciplinary work most resembles.

A final source of conflict resides in what Lakoff calls “Wilensky Law.” This law states that when we form classes, the most natural trend is that more specific knowledge takes precedence over more general knowledge and this trend should be considered when designing classification schemes. Incidence of this law was found in an experiment designed to evaluate the effects of class specificity on the performance of filtering systems [41] Users judged those documents allocated in the more specific categories of the MESH (Medical Subject Headings) hierarchy as more relevant. In an unpublished study, Quiroga and colleagues analyzed hierarchies of bookmarks created by Internet users. Preliminary results indicate that documents tend to be more relevant when they belong to a category located in the middle of a general to specific hierarchy

Another problem implied by the classical theory is that categories are independent of the human who builds the categories. Some researchers contend that there are more than similarities of attributes under consideration when categories are formed and that categorization also depends on who is doing the task and in what context. Research on contextual organizing behavior, is demonstrated by Kwasnik in her doctoral dissertation [24]. She examined how people organize materials when they are not constrained by existing organizational schemes such as those used in libraries. She explored the influence context plays on the processes people use to organize their documents in their own personal information spaces. She interpreted context to include the overall situation of a person, their physical environment, goals, history, expectations, predispositions, time and space constraints, understandings, levels of expertise, and taken for granted (TFG) knowledge. Her underlying assumption was that there is a relationship

between cognitive organization and the organization of physical things, but that there is no one set of organizing principles, as they vary not only from person to person but from one situation to another. In that case, representing TFG knowledge, common sense, and the conditions under which they occur, would be critical for the design of systems that emulate human behavior. After observing how faculty members organized documents in their offices and how they sorted incoming e-mail, Kwasnik [24] found that context was a determinant in the clustering process, with context sometimes taking precedence over the topical attributes of the document.

Donovan’s [17] research on the usefulness of classification schemes suggested that useful classification schemes are those which better conform to users’ organization expectations. Although his research focused on library classification schemes the problems that he found may be significant for filtering systems that model profiles in terms of classes. Donovan argues that a source of deviation of library classification from collocation in the mental spaces of users has its roots in the history of classification that has equated academic disciplines with subject classes. The cross cultural context of a term is ignored and therefore assumptions made to create classes may not be valid outside their original context.

2.3.2. Personal information systems. Malone’s research is an example of a personal information system applied to user interfaces for office automation [30]. Another example is Case’s research in library and information science studies on user needs [12; 13]. These examples exemplify the types of issues being addressed and they show the common goals of eliciting dimensions, content, and structures that individuals use when they organize their own information spaces to facilitate future reference. Therefore, when these individuals look for information in other

spaces, they may expect to find it according to their own models of organization [17]. The motivation for these types of user modeling studies has been to build systems that closely meet user's information organizational expectations.

Malone's research attempted a systematic understanding of how people organize their personal information environments. He was interested in specifications for electronic office systems, collected from a few but deep case studies. His subjects were professional and clerical office workers. Considering that finding information requires three processes; 1) creating classifications, 2) classifying information, and 3) retrieving, he asked the subjects to perform activities involving these three processes. Subjects were asked to give the interviewer a tour of their offices, explaining what information was there and why it was there. At the end, subjects had to find probe documents chosen by coworkers. Results from this study suggest that in addition to finding, reminding (67% of the piles were reminders of things to do) is also important in explaining organizing behaviors. Filing habits are based not only on topics but also on other dimensions such as priority and recency of the documents. There was also evidence that categorizing information presents the major cognitive difficulty when filing information. Difficulties were found not only in naming or labeling the categories but also in allocation of the item in multilevel structures. Piles and files were the two units of office organization that emerged. Piles were aligned with goal oriented situations while files (bookshelves and folders in cabinets) reflected more standardized permanent categories. Piles were organized according to dimensions such as events, priorities, deadlines, current projects, etc., while files were labeled and arranged in systematic order, alphabetical or chronological, by type of document (computer manual, technical reports,

journals), by institutions, by producers of catalogs, by subject, by authors or persons involved. An interesting observation was that in about two - thirds of the retrieval probes the categories used in the description given by coworkers did not correspond to the category used in filing. Malone concludes that difficulties in creating categories (naming) and in assigning (selecting folder/level) may account for problems in retrieving. Electronic office systems can help with these problems by providing intelligent aids for categorizing and performing automatic classification as much as possible. This automatic process could consider, for example, that author and title were the more frequently used categories and that order of creation and update was usually considered by secretaries when multiple levels of categories were involved [30].

Case's research has focused on the information needs and uses of scholars. His initial report describes an exploratory study that compares information storage habits of researchers in the social sciences and in the humanities. The study was framed as a part of broader research on the potential effects of personal computers on scholars' use of information and their working habits. He interviewed 36 professors at a private university in the western United States, asking them to describe the ways they organize their documents. The specific research question was "How do people cope with a heavy intake of printed information?" "How do they acquire, sort, file and prioritize it?" In this study he focused more on the "what" rather than in the "how" and "why," of these questions. His results showed the differences in type of documents (books, journals, notebooks, etc.) and quantity (sizes of piles, drawers, cabinets) employed in humanities versus social science faculty members [12; 13].

Research by Pirolli and Card [38] focused on the application of organization theories in

data mining. Their work exploits the web topology, usage data, and metadata to facilitate information access. They developed the Information Foraging theory to explain how people allocate their attention to understand important information. This theory has been applied to information seeking tasks by presenting users with a clustered navigable overview of the content of a document collection.

Work that examines organization of bookmarks, hot-lists and favorites links is based on organizational behavior and is a source for gathering user preferences for IF systems. Maarek and Shael [28] were interested in automatic bookmark organization by means of the combined approach of automatic classification plus manual user adaptation. Categories used for this organization process were a source for eliciting user interests. Rucker and Polanco [44] implemented a web recommendation system, "Sitseer," whose profile acquisition source comes from bookmarks. The design was motivated by the belief that since saving bookmarks require an intentional act on the part of the user, they may be a reasonably reliable source from which to draw inferences. "Sitseer" considers the organization of bookmarks as an indication of user clustering and grouping behavior, from where it is possible to infer communities of users with similar interests.

Abrams and colleagues [1] see bookmarking as a common strategy for dealing with information overload, as part of the organization of personal web information spaces. They surveyed 322 web users and analyzed the bookmark archives of 50 users to learn why people make a bookmark and how they organized and use them. One of their recommendations is to employ automated filters to improve information re-use and visualization. Kanawati and Malek [22] proposed a collaborative bookmark system, CoWing (Collaborative Web

Indexing system). In this system an agent manages the users' organization as it interacts with other agents to fetch new bookmarks in order to match the needs of their clients. TopicShop, developed by Amento and colleagues [3] is a filtering collaborative system that combines the tools of social data mining with the tools of information workspaces. This system helps users select relevant information and facilitates their organization in order to promote information re-use and sharing. Research examining bookmarks as possible sources of profiles for filtering is currently being conducted at the University of Hawaii. This project includes the evaluation, usability and design of bookmark manager software.

3. Summary

In summary, research in the area of cognitive load contributes to applications such as the effective design of computer-based learning materials, to processes such as information filtering and theories of information organizing behavior. In our discussion of cognitive load and instructional design we described research that can be foundational to the creation of computer-based learning, training, and monitoring environments that can be tailored to individual learner's levels of cognitive load associated with particular tasks. As the research discussed shows, information filtering is essential if we are to reduce cognitive load. More research on building profiles on users' organizational behavior is needed. In addition, we need to know how to better represent contextual information in user profiles.

Filtering techniques are being applied in multiple fields, such as e-business, information retrieval, alerting systems, dynamic electronic mail messaging systems, finance, banking, digital economy and in the communications industry. We believe that an

interdisciplinary approach that incorporates expertise from computer science, information science and educational psychology can be fruitful in providing a foundation of research that influences information filtering and computer-based instructional design.

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