

Book chapter submitted for "Educational Social Software for Context-Aware Learning: Collaborative Methods and Human Interaction"

Title: Harnessing Web 2.0 for context-aware learning: The impact of social tagging system on knowledge adaptation

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ABSTRACT

We present an empirical study investigating how interactions with a popular social tagging system, called del.icio.us, may directly impact knowledge adaptation through the processes of concept assimilation and accommodation. We observed 4 undergraduate students over a period of 8 weeks and found that the quality of social tags and distributions of information contents directly impact the formation and enrichment of concept schemas. A formal model based on a distributed cognition framework provides good fits to the students learning data, showing how learning occurs that emerged from the adaptive assimilation of concepts and categories of multiple users through the social tagging system. The results and the model have important implications on how Web 2.0 technologies could promote formal and informal learning through collaborative methods.

INTRODUCTION

The World Wide Web (WWW) gained extreme popularity during the late 1990s due to its simple architecture and design (Millard and Rose, 2006). The 1990s version of the WWW, now dubbed as Web 1.0 (O'Reilly, 2005), is characterized as "read-only" web. Web 1.0 efforts included content management systems, fixed directory structures and portals that often used client-server architecture. In stark contrast, Web 2.0 is characterized by user-generated content (e.g., blogs, photos), communities of users (e.g., social networks), peer to peer networks (e.g., Napster), and content syndication (O'Reilly, 2005). While the exact definitions of Web 2.0 is open to debate, it is important to note that web applications have evolved into collaborative, user-centered rich internet applications (RIA). The implication of this evolution is significant considering its possible impact in a variety of domains ranging from healthcare (e.g., Kaldoudi et al., 2007), marketing (e.g., Parise and Guinan, 2008), e-Science (e.g., Fox et al., 2007) and education (e.g., Ulrich et al., 2008).

The traditional WWW has been a strong medium for development of the e-learning tradition. The use of traditional web as a teaching and learning medium has led to the development of traditional learning management systems (e.g., WebCT and Blackboard) and also more adaptive intelligent tutoring systems. But an analysis of the use of Web 2.0 technology for teaching and learning is rare (Ulrich et al., 2008). The features afforded by Web 2.0 are in line with educational theories such as constructivism, exploratory learning, and

connectionism, making it extremely interesting instructors, learners and designers. Ferdig (2007) describes four theoretical aspects of Web 2.0 that make it suitable for pedagogy. He argues that Web 2.0 technologies: (a) provide an environment for scaffolded learning (with teachers, peers or an intelligent system), (b) support collaboration, cooperation and shared work resulting in active student participation learning, and (c) provide constructivist learning environments by encouraging students to actively publish, revise and comment on others' content. Alternatively, Ullrich et al (2008) provide technical, social and cultural characteristics of Web 2.0 that make it useful for pedagogy. These include the support for individual creativity and exploratory behavior, usability aspects such as desktop-like interactions, technological aspects such as the use of light-weight architectures and easy modifications, and multiple modes of access (e.g., PC, mobile devices).

Though researchers have claimed the potential usefulness in using Web 2.0 technologies for educational purposes, there are very few studies that explore how Web 2.0 technologies can be effectively incorporated into the public education milieu. One possible reason could be relative newness of the technologies. But, it is interesting to note that several for-profit companies have strongly encouraged their employees to write blogs and develop internal wikis (Ajjan and Hartstone, 2008). Another reason could be the instructors' lack of knowledge or interest in using these technologies or tools in the classroom. Ajjan and Hartshorne (2008) use a survey based study to investigate faculty interest in using Web 2.0 technologies in the classroom in a large public university. They found that faculty are generally aware of the pedagogical benefits of using Web 2.0 technologies. But, more than half of the respondents did not plan to use any Web 2.0 technologies in their classrooms.

Researchers have explored the development and use of Web 2.0 technologies in a variety of domains and tools. One domain that has received attention for Web 2.0 technologies is e-Science projects. Pierce et al (2008) developed outreach tools as a means of creating communities of like-minded researchers. This is an e-Science venture aimed at outreach activity of broadening the participation from minority institutions. Fox et al (2007) examine the usefulness of tagging and social bookmarking for identifying and building keyword-based profiles that can be used for "collaborator match-making services". The system, called Minority Serving Institution-Cyber Infrastructure Empowerment Coalition (MSI-CIEC) incorporates online bookmarking and tagging for researchers. Mason and Rennie (2007) report on the development and use of a range of Web 2.0 technologies that supported the development of a community in Scotland. The social software helped in community interaction, ownership and pride about the local landscape and learning about the local tourist locations.

With respect to the use of Web 2.0 technologies for education, most research reports have focused on design and development of tools. Others have argued about the opportunities for using these tools (e.g., Alexander, 2006). Kaldoudi et al (2008) describe a problem-based learning approach using wikis and blogs for supporting medical education. The authors contrast the lecture-based tradition in medical education with the active, exploratory learning approach that is afforded by Web 2.0 technologies. The authors describe a wiki-blog based system that supports collaboration among medical experts, support strong instructor presence, helped in continuous monitoring of student activities and provided tools for

student inquiry. Takago et al. (2007) describe the ineffectiveness of their e-learning system designed for teaching engineering design. The original design was assembled from independent software components and provided static web content. The new Web 2.0 based redesign is based on analysis of students' learning activities and helps students publish, revise and exchange information. It also helped instructors (and peers) track the progress of the students to give them constructive feedback. Synchronous Learning Environment with Web 2.0 (SLEW) is another application developed with AJAX technology. SLEW is a synchronous distance-learning application that supports dynamic interaction, knowledge sharing and interaction between teachers and learners (Lin et al, 2007). SLEW uses Web 2.0 technology and YouTube API to develop instructional courses for distance learning.

Web 2.0 technologies also face several potential disadvantages. One of the more explored aspects is the challenges Web 2.0 technologies pose for security and privacy (e.g., Ahern et al., 2007; Lam and Churchill, 2007). Recent studies have shown that users are often not sure about the available privacy choices and often are not in a position to make well-informed decisions (Ahern et al., 2007). The openness of Web 2.0 systems is also another potential disadvantage for new users. Bhattacharya and Dron (2007) discuss the challenges of effectively integrating Web 2.0 technologies for pedagogy. They organize the challenges into the following categories: technical challenges confronting the instructor and students, devising effective mechanisms for monitoring the students within and outside the classroom, and learner assessment processes. The authors do not provide any insights about how to overcome these challenges.

The possibilities for using Web 2.0 technologies for pedagogy are endless. But as we can see from the literature, these technologies are still new and there is limited research on how they can be applied to improve context-aware learning. More empirical studies are required to evaluate the challenges in using Web 2.0 in the classroom or at home on a longer-term basis. In this chapter, we will focus on a popular Web 2.0 technology called social tagging. We will first briefly discuss its history and characteristics, followed by a description of an empirical study that investigates how social tagging systems may directly impact concept development. Finally, implications to long-term learning will be discussed.

SOCIAL TAGGING SYSTEMS

Social tagging systems are major Web 2.0 technologies that have gained popularity in recent years. A popular social bookmarking web site is called del.icio.us. Users register and personalize their own collection of bookmarks in their own page. Each bookmark is accompanied by a short description, or tags, of the contents of the site that the bookmark leads to. Users can also see the tags that other users create, search for bookmarks with a certain tags, or browse the collection of bookmarks by other users. Social bookmarking web sites therefore allow a new form of collaborative information discovery and sharing. Users can quickly set up a social bookmarking page for a topic of interest, learn from others who have similar interests, and discover new topics or subtopics and how they are connected to each others.

Alexander (2006) describes the increasing role of social bookmarking in pedagogical applications. He explains their importance in information search and discovery, acting as an "outboard memory", helping in finding collaborators with similar interests and self-reflection

on patterns by evaluating one's own tag clusters. Additionally, it also provides interesting opportunities for evaluating student (or group) progress by tracking their bookmarks and tags. In addition to publicly available social bookmarking systems such as del.icio.us, specific applications have been developed to support user needs in different environments. Examples include the PennTags project (<http://tags.library.upenn.edu/>) and the Harvard H2O project (<http://h2o.law.harvard.edu/index.jsp>). The PennTags project helps online library users at University of Pennsylvania to tag and organize their favorite library resources. The H2O project at Harvard law school creates an online venue for communities to create and exchange ideas through online interaction and discourse.

One major reason why social tagging becomes popular is that people are becoming less satisfied with the Internet being used as a large information database, from which users can retrieve facts easily through powerful search engines. Instead, people are increasingly relying on the Internet to explore and comprehend information, and to share experiences and socialize among other users. The major difference is that Web 1.0 aims at deriving powerful algorithms to index massive amount of information, but Web 2.0 aims at deriving semantic structures among these information that are pertinent to real-world information tasks imposed to real users. For humans, this distinction is not particularly prominent because the human cognitive system naturally conjoins the two functions as we process information. As we will elaborate later, when a person learns to index a new object, such as when learning that a four-leg animal is a cat, the person tends to naturally encode contextual information and classify the object in certain mental categories. When the person encounters an object in the future that is known to be a cat, he or she can then infer only that it has four legs, but also that it meows, has furs, etc. The formation of these mental categories therefore not only allows the cognitive system to capture the structure of the contextual information related to the object, but also allows the cognitive system to capture the similarities and differences across structures in the environment. This is arguably the process that humans can perform much better than computers, and the reason why Web 1.0 fails to satisfy the needs of users. We will come back and elaborate on this point later.

Instead of relying on mental concepts and categories to exploit contextual information, search engines, on the other hand, often rely on automated indexing software to determine the information content of web pages. For example, software such as web crawlers will visit hyperlinks in multiple web sites on the Internet and develop a list of keywords that appear on each of the web pages to which these hyperlinks connect. Eventually, a large database consisting of a master list of these keywords is created. When a user enters a query in the search engine, the words in the query are compared with those in the database. The results of the search are all of the web sites that have been listed under the keywords in the database that match the query words, and the links to these web sites are returned in the order that is determined based on frequency of visits, certain usage histories in the past, location of keywords in the documents, number of other sites that link to each of these web sites, or other features that are believed to increase the likelihood that the information returned from the search engine will match the information goal of the user. Information accessed by this kind of indexed retrieval is often just an *ad hoc list*, with no internal organization at all. Therefore, the fundamental problem with this kind of simple indexing and retrieval is that it does not capture the natural structural relationship among these web sites

based on their information content. Although many online systems do provide classification information such as subject headings in book-selling web sites such as amazon.com, or topics or directories links in search portals such as Yahoo.com, one has to keep in mind that these categories are created by the humans, presumably someone who believe these classification is general enough that they could help users to find information more efficiently. Search engines by themselves, are not very good at generating these classification. In other words, the major drawback of the simple indexing and retrieval in Web 1.0 technologies is that it does not allow users to directly learn the context under which the information naturally appears, thus preventing users to develop the natural structural relationship and classification of information based on the informational structures that naturally exist in our environment.

Social tagging systems, on the other hand, allow collective indexing of the massive information space based on the subjective interpretation of the information in the web pages by different users. Human indexing not only allows better representation of semantics at the level that other humans can easily understand, it also allows multiple interpretation by people with different knowledge background and information needs. The major drawback, compared to automated indexing, is of course the lower speed of processing. However, this drawback seems to be well compensated by the massive volume of users as they provide metadata to the web sites that they find useful and are happy to share with others with similar interests. Indeed, results show that although users may have diverse backgrounds, the dynamics of tags are found to stabilize quickly as the number of users increases (Golder & Huberman, 2006; Cattuto, 2007). This is perhaps one of the most fascinating aspects of social tagging as well as other Web 2.0 technologies, as demonstrated by the success of Wikipedia, or other open-source projects.

With the increasing popularity of social tagging systems, many are hopefully that they can potentially promote learning about social events, beliefs, or concepts that go beyond knowledge acquired from textbooks or formal instructions in classrooms. Although many are hopeful that Web 2.0 technologies may provide a revolutionary way of learning, some researchers question whether this kind of informal learning may only lead only to superficial knowledge acquisition – accumulation of bits and pieces of facts by collective indexing without necessarily developing the deep structural networks of knowledge acquired in formal learning environments. Indeed, most recent studies on social tagging systems have focused on user motivation for contributing to different web sites (e.g., Sen et al., 2006) or aggregate usage patterns in specific web sites across a specific period of time (e.g., Cattuto, Loreto, & Pietronero, 2007; Golder & Huberman, 2006). To a certain extent, many of these studies have treated social tagging systems as a form of technology that provides more meaningful indexing of information than automated indexing by search engines. To our knowledge, no empirical study has been done to investigate how the interactions with social tagging systems may potentially influence higher-level cognitive structures and promote “real” learning beyond indexing of information. To illustrate this point, we will first review the ideas of distributed cognitive systems before we present our study that directly test how social tagging systems may directly influence learning.

Social Tagging Systems as Distributed Cognitive Systems

Social tagging systems are excellent examples of distributed cognitive systems (Hollan, Hutchins, & Kirsh, 2000; Hutchins (1995); Zhang & Norman, 1994). In contrast to the traditional definition of cognition, a distributed cognitive system encompasses all flow of information among individuals and the resources in the environment. The idea is that when one examines the outcome from the distributed cognitive system, one cannot easily attribute the outcome to any isolated component of the system. In fact, the basic premise of the distributed cognition framework is that behavior arises out of the interactions of the components of the system, and the functional unit of analysis of behavior in a distributed cognitive system should include all elements that bring themselves into coordination to accomplish some tasks, and any isolated analysis of its parts is insufficient to understand how the system works. A classic example is the demonstration of distributed memory systems in the cockpit by Hutchins (1995), who showed that the encoding and retrieval of critical information by pilots rely on various displays inside the cockpit as much as individual memory. In addition, information from the external environment provides more than simply a cue to internal memories, but provides opportunities to reorganize the internal and external representations in the distributed cognitive system.

Under this distributed cognitive systems framework, the current analysis of social tagging systems will focus on the intricate interactions between internal and external representations of concepts, tags, and documents as a user is engaged in as they interact with the system. **Figure 1** shows a notational diagram of this theoretical framework. Multiple users have their internal representations of the world, as they interact with the social tagging systems and consume information on different web pages. These internal representations partially reflect the different background knowledge of different users, as well as differences in their information needs. These internal representations will influence how they interpret the information in different web pages, the tags created by others, as well as the tags they will create to associate with the web pages that they visit. To a certain extent, these internal representations are shared among each other through the external representations (tags) of the information contents of the web pages. Not only that users may contribute tags to different web pages, but the interpretation of tags created by others may also influence their own internal representations as some forms of knowledge adaptation. The major characteristics of this distributed cognition framework is that: (1) both internal and external representations may influence the search and interpretation of the web document, and (2) the understanding and interpretation of the web document may influence both the internal (concepts) and external representations (tags).

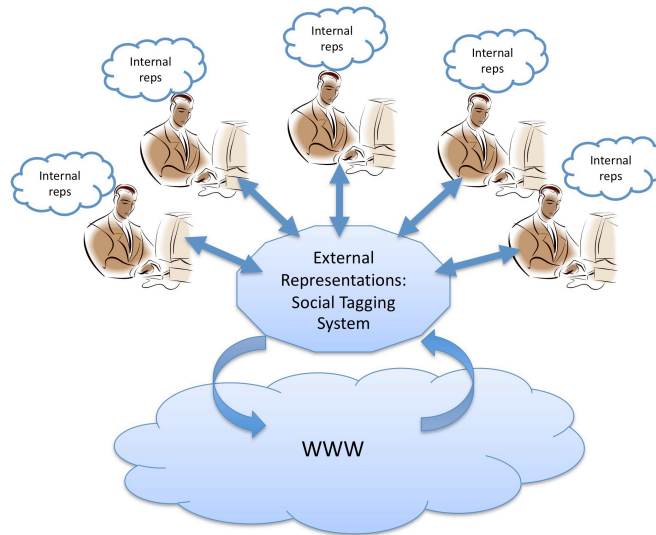


Figure 1. A distributed knowledge representations framework in a social tagging system (reps = representations).

Tagging and Knowledge Adaptation

Researchers in cognitive science have proposed different representational structures to capture the properties of our general knowledge of objects around us, and one prominent representational structure is called a schema (e.g., Rumelhart & Ortony, 1976). Schemas represent our concepts of objects such as their attributes and their categorical relationship. For example, we know that houses have rooms, can be built of wood or stone, serve as human dwellings, and are a type of building. The importance of the category information is that it stores predictable information about instances of a category, such that when someone mentions a house we have a rough idea of the object being referred to. Note that schemas represent knowledge at an abstract level, in the sense that they encode what is generally true rather than what is true about specific instance.

One important property of schemas is that there are default values for certain schema attributes, which are presumably developed from our past experiences. This provides schemas with a useful inferential mechanism. Many studies have been conducted to confirm the psychological reality of schemas. For example, Brewer and Treyens (1981) conducted a study in which participants were told that they were in an office. After a short period of time, participants were asked to recall objects in the office. Results showed the participants were much better at recalling objects that can typically be found in an office than those that are not. In addition, participants mistakenly recalled objects (such as books) that can typically found in an office, but were in fact not in the specific office that they were in. These studies show that when given a hint to what the object belongs to, people will utilize their existing knowledge to infer the other “hidden” attributes of the object.

As people interact with their environment and acquire more experiences their schemas may be modified to make sense, or used to make sense of the new experiences. This process of knowledge adaptation can be traced all the way back to the Piaget (1975)’s developmental model of equilibration of cognitive structures in children. According to Piaget, there are at

least two processes through which new experiences interact with existing schemas. When new experiences are modified to fit existing schemas the process is defined as assimilation. In contrast, accommodation is an adaptation process of knowledge acquisition that changes the schemas in order to fit the new experience, or the person creates an entirely new schema in order to accommodate new data that does not fit any of their existing schemas. Through these processes of assimilation and accommodation, people can adapt to new experiences that they obtain from their interactions with others, such as when they discuss, share, or exchange information.

Consider the case when a user is browsing for information related to a broad topic of interest, such as when one is interested in knowing more about facts or events related to the independence of Kosovo. We called this an ill-defined information task (as opposed to well-defined task in which a specific piece of information is needed such as looking for the address of a hotel), in which one only has a rough idea about what they are looking for, and the information goal itself will be refined throughout the search process. During the search, social tags created by others can be utilized as useful cues to select and navigate to the documents pertaining to the topic of interest (Marchionini, 2006; White, Kules, Drucker, & Schraefel, 2006). Through this process of *exploratory search*, the user gains a better understanding of the topic through the enrichment of internal representations of concepts relevant to the topic (either assimilation or accommodation, or both). The user may then create their own tags for the web documents based on their own understanding as well as the existing social tags, and may choose to perform another cycle of exploratory search, refinement of concepts, and so on. *In other words, through iterative exploratory search cycles, the interactions between internal concepts and external tags gradually lead to sharing and assimilation of conceptual structures as more and more people assign social tags to represent ideas or concepts that they extract from the massive amount of web documents.*

Applying the above framework of knowledge adaptation to social tagging, we have three specific predictions on how social tags may influence knowledge development. First, the ability to predict based on category membership is presumably the major utility of tags that are assigned to a bookmark. Tags invoke certain internal schemas of the user, and these schemas allow the user to predict what information is “hidden” in the web page that the bookmark leads to. It follows that the higher the “quality” of tags (in the sense that they allow better prediction of the underlying schemas), the more efficient will the user be able to find the right information. Second, given an information goal, when there are more high-quality tags that match the existing schemas of the user, the existing schemas of the user will be richer through the process of assimilation. Third, when information contents are more diverse, more distinct schemas will be developed through the process of accommodation. We will formalize these processes in our next section.

A Formal Model of Social Tagging under the Distributed Cognition Framework

To formalize the analysis of social tagging, we will present a probabilistic model of exploratory search behavior as users interact with a social tagging system. The formal model allows not only allows precise predictions on behavior, but also provides clear characterization of how different components and processes influence behavior. The model assumes that people will naturally categorize web documents as they go through and

comprehend them (with the tags helping by adding additional features), and *the reason why mental categories (schemas) are formed is that this is an adaptive response to the inherent structure of the stimuli from the external world to our minds that allow humans to predict features of new objects better*. Tags assigned to documents are just another set of features that allow us to predict the unobserved contents of the documents, and with the formation of mental categories, the tags will not only inform the user what they literally refer to, but also other unobserved features of the documents.

Assume that a user has a set of schemas S and a set of semantic topics T . The information goal is to predict whether topic T_j (some useful information) can be found by following a link with tags G , i.e., the user is trying to estimate this probability: $P(T_j|S, G_k)$ when deciding on links, which can be broken down into two components based on the distributed cognition framework. One component predicts the probability that a particular topic can be found in a given schema, and the second component predicts the probability that a given set of tags are associated with a given schema:

$$P(T_j | S, G) = \sum_m P(S_m | G) P(T_j | S_m)$$

(Eqn1: Likelihood of finding topic T_j given schemas S , and tags G)

In other words, to predict whether topic T_j can be found in a particular document, one can first estimate $P(S_m|G)$: the probability that the document with tags G belongs to a particular schema S_m . This estimate depends on how much the internal and external representations match each other: The higher the match, the better is the model able to predict to which categories the document belongs. It also provides a measure of the “quality” of tags, as it indicates how much the tags may help invoke the set of schemas in the user. The second estimate $P(T_j|S_m)$ is the probability that topic T_j can be found in schemas S_m . This estimate therefore depends on the relationship between the tags and the schema. The overall probability $P(T_j|S, G_k)$ can then be estimated by enumerating the product of these two probabilities over all mental categories.

Assimilation: Enrichment of mental categories

If we assume a set of schemas that people may have, one can first estimate the prior probabilities for each of these schemas, and calculate how likely a tag created by a user is created based on a particular schema by the Bayes theorem. Specifically, if $P(S_m)$ is the prior

probability of schema S_m , and $P(G|S_m)$ is the conditional probability that tag G belongs to S_m , then we can obtain:

$$P(S_m | G) = \frac{P(S_m)P(G|S_m)}{\sum_m P(S_m)P(G|S_m)}$$

(Eqn 2: Probability that a document with a tag G is created from schema S_m)

To estimate the prior probability, one can assume that there exists a prior probability for any two random objects (e.g., documents) to belong to the same schema in a particular (informational) ecology. The higher the value of this prior probability, the lower the likelihood that any two objects will belong to a new schema. For the current purpose, we assume that the prior probability that any two web documents belong to the same category for a particular information task. The prior probability therefore depends on the general structures of the information distribution and the information goal. For example, the top of **Figure 2** shows a notational diagram of 5 topics (A, B, C, D, & E) in a given information space, and these topics have some levels of overlap in their information contents. Assume that for information task X, topics A, B, & C are relevant. The information space becomes highly overlapped (bottom left of **Figure 2**). However, for information task Y, topics D and E are relevant, and the information space contains topics that have low overlap. Therefore given the same information space, information task X will have a higher prior probability that any two relevant documents will belong to the same schema, but for information task Y, the same prior probability will be lower.

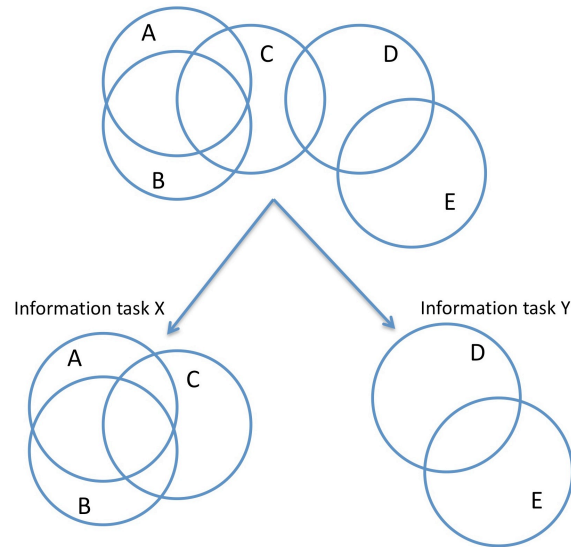


Figure 2. Notational diagrams showing the original information space (top), and the information space for relevant topics for information task X (left) and Y (right). Each circle represent a topic.

The conditional probability $P(G|S_m)$ can simply be estimated by the ratio of the number of members in schema S_m that contains G and the total number of members in G , i.e.,

$$P(G|S_m) = n/n_m \text{ (Eqn 3: Probability that a tag belongs to mental category } m\text{).}$$

When the model is browsing different documents and their corresponding tags, estimates of how these tags may come from any of the existing schemas can be derived by calculating the value of $P(S_m|G)$ for each m . The schema that has the highest value of $P(S_m|G)$ can then be selected, and refined based on Eqn 3. As more and more documents are processed, the new experiences will be assimilated with the existing schemas of the person and the existing set of schemas will be enriched through this process.

Accommodation: Formation of new mental category

It is possible that a person may encounter a new piece of information that does not fit into any of his or her existing schemas. In that case, the existing set of schemas need to be adjusted to accommodate for the new piece of information. This decision was based on the value of $\max[P(S|G)]$, where G represents the contents and tags of the document and S represents the set of existing schemas, and the max operation is performed in the set S . Specifically, a new category will be created only if

$$P(R_{new}) > \max[P(R|S)] \quad (\text{Eqn 4: New mental category})$$

i.e., the probability that the document belongs to a new category is larger than that for it to belong to any of the existing schemas. If this condition is met, a new schema will be created. The accommodation process therefore allows new schemas to be formed from new experiences.

Assigning tags to a bookmark of a web document

Given an existing tag G_k , the model will calculate the value of $P(G_k|S_m)$, where S_m is the category to which the current document is assigned according to Eqn 3 & 4. The model will assign this tag G_k to this document only if

$$P(G_k|S_m) > \tau_{threshold} \quad (\text{Eqn5: Assigning an existing tag})$$

where $\tau_{threshold}$ is a free parameter to be estimated from the data. A new tag is created only if any of the tags associated with the documents in category S_m is larger than the maximum of $P(G/S_m)$ for all existing tags, i.e.,

$$P(G_{new}|S_m) > P(G_{max}|S_m) \quad (\text{Eqn6: Assign a new tag})$$

Note the model does not predict which particular tags will be used, it only predicts how likely existing tags will or will not be used based on the relationship between the tags and the predicted mental categories formed.

The empirical study

The main purpose of The empirical study is to test to what extent interactions with a social tagging system will directly impact knowledge adaptation. In addition, precise protocol data were collected to verify the predictions made by the model, which specifies both the assimilation and accommodation processes that underly knowledge adaptation. A set of ill-defined information tasks was chosen. In all tasks, undergraduate students were given a rough description of the topic and gradually acquire knowledge about the topic through an iterative search-and-comprehend cycles. Students were told to imagine that they wanted to

understand the given topic and to write a paper and give a talk on the given topic to a diverse audience. Two general topics were chosen: (1) “Find out relevant facts about the Independence of Kosovo” (IK task), and (2) “Find out relevant facts about Anti-aging” (AA task). These two tasks were chosen because the IK task referred to a specific event, and therefore information related to it tended to be more specific, and there were more Web sites containing multiple pieces of well-organized information relevant to the topic. The AA task, on the other hand, was more ambiguous and was related to many disjoint areas such as cosmetics, nutrition, or genetic engineering. Web sites relevant to the IK task have more overlapping concepts than those relevant to the AA task. The other characteristic is that because the AA task was more general, the tags tended to be more generic (such as “beauty”, “health”); in contrast, for the IK task, tags tended to be more “semantically narrow” (such as “Kosovo”), and thus had higher cue validity than generic tags.

Participants

4 participants were recruited from the University of Illinois. Participants were undergraduate students and all had extensive experience with general information search and the del.icio.us Web site. Participants were randomly split and assigned to one of the tasks. From their self-reports they were all unfamiliar with the given topics. Participants were told that they should explore all relevant information to comprehend the topic using either the search function in del.icio.us or any other Web search engines, and they should create tags for Web pages they found relevant to the topic and stored them in their own del.icio.us accounts. Participants were told that these tags should be created for two major purposes. First, these tags should allow them to re-find the information quickly in the future; second, these tags should allow their colleagues to utilize the relevant information easily in the future.

Procedures

Each student performed the task for eight 30-minute sessions over a period of 8 weeks, with each session approximately one week apart. Students were told to think aloud during the task in each session. All verbal protocols and screen interactions were captured using the screen recording software *Camtasia*. All tags created were recorded manually from their del.icio.us accounts after each session. Students were instructed to provide a verbal summary of every Web page they read before they created any tags for the page. They could then bookmark the web page and create tags for the page. After they finished reading a document, they could either search for new documents by initiating a new query or selecting an existing tag to browse documents tagged by others. This exploratory search-and-tag cycle continues until a session ended. All tags used and created during each session were extracted to keep track of changes in the shared external representations, and all verbal description on the Web pages were also extracted to keep track of changes in the internal representations during the exploratory search process. These tags and verbal descriptions were then input as contents of the document.

One week after the last session, participants were asked to come back to perform a sorting task. Participants were given printouts of all web pages that they read and bookmarked during the task, and were given the tags associated with the pages (either by themselves or other members in del.icio.us). They were then asked to “put together the web pages that go

together on the basis of their information content into as many different groups as you'd like". The categories formed by the participants were then matched to those predicted by the assimilation and accommodation processes in the rational model.

Results

Participants on average created 88.5 bookmarks (IK1=93, IK2=84) and 379.5 tags (IK1=392, IK2=367) for the IK task, and 58 bookmarks (AA1=52, AA2=64) and 245 tags (AA1=256, AA2=234) for the AA task. Participants in the IK task created more bookmarks and assigned more tags than those in the AA task, but the average number of tags per bookmark is about the same (4.3 tags per bookmark) for the two tasks. As expected, finding relevant information for the AA task is more difficult, as reflected by the fewer number of bookmarks created. Given that distribution of information was more disjoint in the AA task (e.g., there is little overlap of information between web sites on skin care and genetic engineering), the results were consistent with the assumption that the average rate of return of relevant information was lower for the AA task than the IK task.

Figure 3 shows the proportion of new tags created by the participants (left) and model (right). Perhaps the most interesting pattern was that even though participants assigned fewer tags, but the *proportions* of new tag creation over total number of tag assignment were higher in the AA task than in the IK task. This was consistent with the lower rate of return of relevant information in the AA task, and this lower rate was likely caused by fact that the existing tags on del.icio.us was less informative for the AA task. Indeed, concepts extracted from the documents by the participants in the AA task were more often different from the existing tags than in the IK task, suggesting that the existing tags did not serve as good cues to information contained in the documents. The general trends and differences between the two tasks were closely matched by the model ($R^2=0.75$). Again, the major mismatches were found in the first sessions, where the model tended to under-predict the creation of new tags, especially for the IK task. A model that randomly assigns tags was created and compared to performance by humans and model. Chi-square tests show that both human and model performance was significantly different from the chance model ($p<0.01$), showing that they are significantly above the chance level.

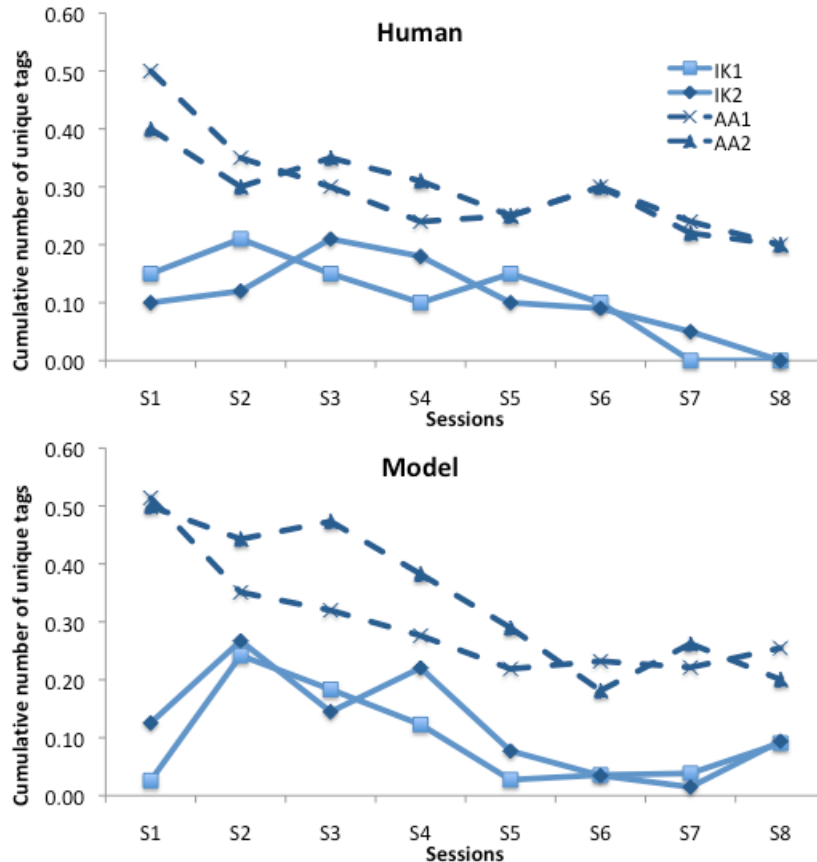


Figure 3. Proportions of new tags created over total number of tags assigned across the 8 sessions by the students (top) and models (bottom).

Formation of mental categories

One core assumption of the rational model was that the assignment of tags and the selection of links were both based on the set of mental categories formed from observing existing tags assigned to documents that they processed. It is therefore critical to verify that the set of mental categories formed by the model match those formed by the participants. To do this, correlations between the mental categories formed by the model and the participants were calculated by constructing “match” tables for each participant and model. Items that are in the same category will be given a value 1, otherwise a 0. For example, two possible categorization for the set {a,b,c,d,e} are {ab}, {c,d}, {e} and {a,b,c}, {d,e}. In that case, their correlation can be calculated as $r=0.102$ based on the match table.

The major determining variable for mental category formation in the model is the value of the coupling parameter, c (see Eqn6). This was set to 0.6 for the IK task and 0.3 for the AA task to best fit the data. Because the information distributions are more disjoint for the AA task, the value of the prior probability of $P(S)$ was set to a higher value. **Table 1** shows the number of categories formed by each participants and model, as well as their correlations. As predicted, participants formed more categories in the AA task, reflecting the structures of the information sources. However, as shown earlier, participants in the AA task had lower rate of return in their information search, suggesting that they spent more time looking for relevant information. Although the number of categories formed was higher in the AA task, the quality of these categories (in terms of

how much they help in finding information) was lower than those in the IK task (results shown next). The correlations between the participants and the models were high in both tasks, suggesting that the model roughly formed similar mental categories as participants, even though the inherent information structures were different between the two tasks.

	#categories (Students)	#categories (Models)	Correlations of the partitions
IK1	6	6	0.71
IK2	5	6	0.68
AA1	12	13	0.59
AA2	10	11	0.67

Table 1. Number of categories formed by each participant and model, and the correlations of the partitions of the categories of the models and the students calculated using the match tables.

DISCUSSION

From our knowledge, the current study is the first that shows social tagging systems not only can facilitate dissemination of information, but can also induce cognitive changes such as knowledge adaptation. The current results also show that social tagging systems have the potential to facilitate not only collaborative indexing of the massive amount of information, but also as a means for social exchange of knowledge structures, and thus has the potential to promote formal or informal learning of diverse topics and the development of common schemas or understanding within or across different communities. Given the direct impact on the development and refinement of mental schemas, it is not hard to imagine that social tagging systems could also impact collaborative activities that involve higher-level cognitive processing, such as problem solving, decision making, or creative designs. Indeed, many innovative ideas were generated by the sudden realization that knowledge structures in disjoint domains are relevant. It seems that we have only started to harness the potential of socio-technological systems, especially in the area of education.

The formal model was developed under the assumption that humans adapt their knowledge schemas through the assimilation and accommodation processes as they explore the Internet and comprehend knowledge extracted from web documents. The model, developed under the distributed cognition framework, was successful in providing good quantitative predictions on the emergent behavior of four different individuals across an extended period of time. The model shows how internal representations slowly assimilate to the external informational distribution through the processing and assignment of social tags, and how individuals create new tags based on their internal representations. The dynamic interactions between internal and external representations captured by the model has also highlighted the value of the distributed cognition framework, as they imply that isolated analysis of either the distributions of external tags or cognitive mechanisms of the user will unlikely lead to good characterizations of the dynamics that emerge from socio-technological systems.

The formal model also provides direct design guidelines for future social tagging systems. For example, the formal analysis of the current distributed cognitive system can be implemented as software tool that facilitates extraction and exchange of mental categories

for different groups of people who have different expertise in different domains. Can tags, for example, be organized by mental categories extracted from experts in different fields in ways that facilitate knowledge transfer? Will transfer or exchange of knowledge at the fact, concept, and category levels facilitate innovation because they encourage re-structuring of existing knowledge structures? The delicio.us system in this study was a general-purpose social tagging system. The current results suggest that social tagging systems can be specialized for different purposes. For example, to facilitate context-aware learning, perhaps the systems can be combined with knowledge engineering software that extracts and classify knowledge according to top-down domain knowledge to facilitate knowledge adaptation.

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