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Using the Social of Tagging: The Interplay of Social Tags and the Strength of Association in Navigation and Learning Processes

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Abstract

When people navigate through the World Wide Web they choose their path of navigation based on their prior knowledge. This may be problematic when users have a deficient knowledge leading them to suboptimal information. In this study we examined how the externalized knowledge of social tags can be used to change navigation behavior and to trigger learning processes. In an online experiment with 531 participants we investigated the effect of the individual strength of association on navigation processes, and how the collective strength of association, visualized in tag clouds, may affect individual navigation and the strength of association. Results showed the effect of individual strength of association on navigation behavior, selection time and recognition. Furthermore, we found that the collective strength of association affects navigation behavior and triggered incidental learning processes, leading to a change of individual strength of association.

Keywords: social tagging; tag clouds; social software; information foraging; web search; incidental learning

Introduction

People frequently use the World Wide Web for information and product search. In some topic domains, Web users may only possess deficient prior knowledge and an incomplete view of relevant aspects. A user's knowledge may, however, be critical for the search process and the information which is retrieved from the Web. The Web offers enormous quantities of heterogeneous information and products, and each user will have to select between different links and keywords for finding relevant resources. When users follow navigation links based on their deficient prior knowledge these may lead to information which will confirm or even reinforce the deficient knowledge of that user. For example, users might associate the treatment of a disorder with some specific medication. Instead of considering other treatments or medications a user may quickly select a navigation path leading to information which reinforces potentially deficient knowledge saying, for instance, that a specific medication is the only reasonable treatment. This might happen when navigating to a website from a pharmaceutical company.

So, on the one hand, the mass and the diversity of resources available on the Web is combined with the risk that people might select suboptimal information or products. On the other hand, new tools may provide the opportunity to use the mass of available information on the Web to improve individual navigation and to adjust and change the users' previously deficient prior knowledge. In this paper we address the research question how social tags, as emerging collective information, can affect the individual process of navigation and how social tags trigger learning processes during navigation. In particular, we focus on situations in which the externalized knowledge of social tags contradicts the prior knowledge of users.

The next chapter will provide a theoretical overview on Web navigation and its interrelation with spreading activation, followed by an overview on social tagging and how it may interact with cognitive processes. As a next step we will present an experimental study on the effects of social tags and the strength of association on navigation and knowledge acquisition.

Theoretical Background

Information Foraging Theory

A pivotal cognitive theory of Web navigation is the Information Foraging Theory (Pirolli, 2007; Pirolli & Card, 1999). It explains selection processes of links and navigation paths on the Web, the so-called "information foraging". Taking for granted that many search tasks on the Web require browsing activities in order to find a desired resource (Marchionini, 2006), users will have to select between different links and navigation paths. They will have to decide which link may lead to a desired – and not directly accessible – distal resource, say, a piece of information on some Web site. When navigating the Web users have to make judgments based on proximal cues (e.g., links) and assess which of these cues have the highest likelihood of leading to a desired distal resource. One of the core concepts of the Information Foraging Theory is the so-called "information scent" of links. The information scent describes the subjective usefulness of links for navigation. Links with a subjectively high probability of leading to a desired distal resource have a high information scent and are very likely to be selected in the search process. How will users estimate the information scent of links?

Spreading Activation Understanding how people evaluate the information scent of a link is closely related to models of semantic memory and spreading activation (e.g., Anderson, 1983; Collins & Loftus, 1975). Cognitive models of semantic memory assume that memory is based on a collection of cognitive structures, so-called “chunks”. These are organized as nodes in a large network in memory. Each of the chunks is connected to other chunks with a different strength of association. The strength of association derives from the respective individual’s previous learning experiences. When two chunks frequently co-occur in a meaningful context, the association between these chunks becomes stronger. For example, when Valium is often mentioned in the context of anxiety disorders, a high strength of association will be established. The strength of association is important in the process of retrieving chunks from memory. To retrieve a chunk from memory, it must be activated by other chunks. The activation spreads from one chunk to another, and the stronger the association, the higher is the likelihood of exceeding a certain level of activation for a chunk. For instance, the activation of Valium in the context of anxiety disorders is facilitated by a high strength of association.

In a search process a desired distal goal activates connected chunks in semantic memory. Based on the strength of association of connected chunks and the resulting strength of activation, users estimate the information scent of links: when a chunk receives a high spreading activation through a search goal, the corresponding link receives a high information scent, too. For example, when the chunk Valium is highly activated by a search goal, e.g., treatment for anxiety disorder, then the corresponding Web link Valium would also have a high information scent for a user.

Research on Navigation Processes Several studies have demonstrated the effect of the information scent on Web navigation (e.g., Blackmon, Polson, Kitajima & Lewis, 2002; Fu & Pirolli, 2007; Pirolli, Fu, Reeder & Card, 2002). These studies have mainly used cognitive modeling of Web navigation and validated them against actual user data.

In these studies, differences in prior knowledge were not considered for the modeling process. In some studies, for instance, the simulation of strengths of association and the resulting information scents were based on the same large text corpora and the co-occurrence of words within these texts (Fu & Pirolli, 2007; Pirolli et al., 2002). So the focus of these studies did not lie in investigating the effects of differing prior knowledge, but rather in modelling the general search process for specific search tasks. Another aspect which has not been investigated in more detail within the (non-social) context of these studies is learning processes during navigation, i.e. incidental learning as a by-product of navigation. When navigating the Web, users process information in order to assess the information scent of links. But the choice of the navigation path is not only a means to an end. It may also be of importance what happens “along the path”. Except for one study showing incidental category learning during navigation (Pirolli, 2004) it remains unclear how navigation itself could change the strength of association of chunks through incidental learning processes.

The question of learning is particularly interesting in a social Web context, in which large numbers of other users contribute information and, in particular, in which this information can be used for navigation processes. New Web technologies, like social software tools, provide this opportunity. Social tagging systems make it possible to learn from the externalized knowledge of a community. In the next section we will give an overview on social tagging and relevant studies that have been conducted in this field of research.

Social Tags

Social tagging is the activity of annotating digital resources, e.g. bookmarks, pictures or products, with keywords, the so-called “tags”. Tags represent metadata on resources. For most applications each user can choose individual tags for stored resources. Tags reflect individual associations with resources and are based on the specific meaning or relevance to that user. At the individual level, tags will help users to structure, organize and find their own stored Web resources. In a social context, tags offer the opportunity to use other users’ navigation links for search processes. Moreover, social tagging systems can aggregate the tags of individual users. In this way, resources are described by the community in a “folksonomy”, developed in a bottom-up process of individual tagging. The aggregated tags represent an emerging collective knowledge of Web users. These aggregated tags can also be used as links for individual search processes. In a social tagging system, the community creates a network of connections between resources and tags. The connection between a resource and a tag becomes stronger when tags for that resource are used more frequently by many users. The connection between two tags becomes stronger when both tags are used together for one resource: the more often two tags co-occur with the same resources, the stronger they are related to each other. When aggregating all tags from a community, a representation of the connections between related tags and their strength of association will emerge. Typically, tag clouds visualize these associations and their specific strength: The font size of tags illustrates the strength of association of tags to a related tag or a resource (see Figure 1).

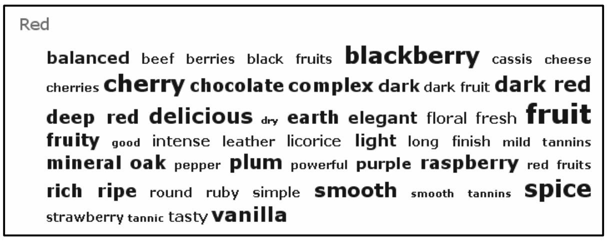

Figure 1: A tag cloud representing tags related to “red wine” (from vinorati.com). The font size visualizes the strength of association between “red wine” and the tag.

Social tagging systems may be regarded as shared external knowledge structures of communities (Fu, 2008). They can externalize the connections of tags and their specific strength of association in tag clouds. Because these associations are based on the collective tagging behavior of a community, they can also be considered to be the externalized associations of a particular community. The structure of social tagging systems even constitutes an analogy to spreading activation processes in semantic memory models, in which tags represent the nodes of a large network. When a tag is selected – or activated –, the activation spreads from this tag to others, and the related tags and their strengths of association can be visualized in tag clouds.

So far, research on social tagging has mainly focused on the description of regularities of tagging systems (e.g., Golder & Huberman, 2006) or the use of tagging systems (e.g., Millen, Yang, Whittaker & Feinberg, 2007). But, as stated by Fu (2008), surprisingly little is known about how these new technologies, like social tagging systems, may directly interact with individuals at the knowledge and cognitive level. Some studies have investigated the influence of tag clouds on visual attention, recognition and tag selection (Bateman, Gutwin & Nacenta, 2008; Rivadeneira, Gruen, Muller & Millen, 2007). But these studies focused primarily on the visual features of tag clouds and did not address aspects of collective knowledge, as it is externalized in social tagging systems and tag clouds.

A study investigating the interplay between the collective knowledge of a tagging system and the individual cognitive level was presented by Fu in 2008. He presented a rational model of social tagging and provided evidence for the interaction of social and cognitive systems. That study showed the impact of externalized knowledge structures on individual learning processes, especially the formation of mental categories, but did not focus on the effects of the representation of knowledge, externalized in the form of tag clouds, on individual navigation behavior and the strengths of associations. A further study, which also investigated the knowledge exchange within tagging systems dealt with the question of how social tags affect tag choice (Kang, Kannampallil, He & Fu, 2009). This study also showed that the externalized knowledge of social tags will influence individual behavior: users adapted their tag choice to the collective structure of the social tagging system.

Research Questions and Hypotheses

Models of Information Foraging (Pirolli, 2007) assume that processes of spreading activation are crucial for the navigation behavior of users. So the strength of association between a search goal and available links plays a critical role in the selection of navigation paths. We assume that users with deficient prior knowledge are likely to choose navigation links that lead to suboptimal resources. So we manipulated the users' prior knowledge and investigated the impact of individual strength of association on navigation processes.

The main goal of this study is to investigate how the collective knowledge of a community affects individual learning and navigation processes. Can social tags be used to change the navigation behavior of users? Will users learn from the collective knowledge during navigation, and will they improve the deficits of their prior knowledge accordingly? Apart from the variation of the users' prior knowledge we also manipulated the strength of association of tags. In our experiment we created a situation in which the individual strength of association contradicts the collective strength of association. We examined the effect of collective strength of association on the change of individual navigation and strength of association.

We expected (1) a main effect for both the individual strength of association and the collective strength of association on navigation behavior. Secondly, we expected (2) an incidental learning process and a change of individual strength of association during navigation through the collective strength of association. Thirdly, we expected that (3) in a situation of highly contradicting individual and collective strengths of association, users will perceive a conflict and process all tags more thoroughly and spend more time on their selection of tags.

Experiment

Method

Participants 531 participants (179 female, 352 male; mean age 28.94 years, *SD* = 9.36) were recruited on Amazon Mechanical Turk (mturk.com), an Internet marketplace for engaging users in online micro-tasks. The participants were paid US-$1.20 for the experiment. The participants came from 52 different countries. Most of the subjects lived in the United States (41.1%) and India (36.7%).

Materials and Procedure In order to ensure that we could actually manipulate the prior knowledge of subjects, we selected a topic which was very likely to be mainly unfamiliar to the subjects: wine from the Asian country of Georgia, in particular from various wine regions of Georgia. The experiment was set up online and all participants could perform the task from a computer with Internet access. On average, the experiment took about 8 minutes for each user. We instructed the subjects that our aim was to receive feedback on the design of Web sites dedicated to wine. The actual goal of the task in the experimental context was not transparent to the subjects. We did not inform them before or during the task that we were actually measuring navigation and learning processes.

The task consisted of two parts. In the first part subjects had to provide feedback on design features of a wine list from "a pilot user who is a wine lover of Georgian wines". The list was presented to the subjects for 30 seconds, followed by five questions on the design of this list in order to direct attention to it. The first independent variable - the individual strength of association - was manipulated by this wine list (see Figure 2).

The second part was a navigation task. In this part, subjects were asked to use tag clouds as navigation links. The subjects were told that the tags originate “from different sources of the Internet, like online wine communities and wine retailers”. After a basic introduction to social tags, subjects were presented tag clouds and were asked to click on one tag of each tag cloud that was most appropriate to direct them to a typical Georgian wine. Overall, we presented four tag clouds. The first and the third tag cloud were used as case examples. Only the second and fourth tag cloud were relevant to the experiment. In each condition these two tag clouds were identical. These tag clouds represented related tags (wine regions) to Georgia (see Figure 3). After having clicked on a tag, it was color-marked and two seconds later the next tag cloud appeared. The next tag cloud was independent of the previous selection. Only tag clouds were presented, no corresponding resources were displayed. After the navigation task we presented tests measuring the dependent variables “decision” and recognition.

Independent Variables and Design A 5 x 4 between-subjects design was used. Subjects were randomly assigned to one of the 20 conditions. As a first independent variable we experimentally manipulated the individual strength of association by varying the content of the wine list, which was presented to the subjects in the first part of the task. We manipulated how strongly users associate the wine region “Kakheti” with Georgian wine. Users were presented a wine list with five Georgian wines. In the different conditions the number of wines coming from the region “Kakheti” was varied. The independent variable had five continuous levels: wines from the region “Kakheti” were either (1) not part of the list (see Figure 2a); or (2) one time; (3) two times; (4) three times; or (5) four times in the list (see Figure 2b).

a) b)

Figure 2: Wine lists manipulating the individual strength of association for the “Kakheti” region, representing the lowest and highest levels: a) “Kakheti” is not part of the list b) 4 of the 5 wines come from “Kakheti”.

As a second independent variable we experimentally manipulated the collective strength of association by varying the tag size in the tag clouds. Except for the tag “Kakheti” none of the regions presented in the wine list reappeared in the tag clouds. We manipulated how strongly the fictitious tagging community associates the wine region “Imereti” with Georgian wine by varying the tag size of “Imereti”. The other tags did not vary in size. The independent variable had four continuous levels: (1) the tag “Imereti” had the same size as the tag “Kakheti” with both tags representing the biggest tags in the tag cloud (see Figure 3a); (2) the tag “Imereti was 33% bigger than in the first condition; (3) the tag “Imereti” was 67% bigger than in the first condition; (4) the tag ”Imereti” was 100% bigger than in the first condition (see Figure 3b).

a)

b)

Figure 3: Tag clouds manipulating the collective strength of association for “Imereti”, representing the lowest and highest levels: a) “Imereti” has the same size as “Kakheti” b) “Imereti” is twice as big as “Kakheti”.

Dependent Measures As dependent variables we measured the navigation behavior of users for the two relevant tag clouds (wine regions) by analyzing the logfiles. It was assessed how often users clicked the tag “Kakheti” (for which the individual strength of association was manipulated in the wine list) or the tag “Imereti” (for which the collective strength of association was manipulated in the tag cloud). Accordingly, the number of clicks for navigating the two tag clouds could range between 0 and 2 for either of the dependent variables “Navigation Kakheti” and “Navigation Imereti”. We also measured how much time users spent for the selection process. We added the time which was used for navigating each of the two tag clouds.

For the assessment of the dependent variable “decision”, users were asked which Georgian wine region they would select if they had to buy a typical wine from Georgia. They had to choose between the alternatives “Kakheti” and “Imereti”. Referring to the fluency heuristic (e.g., Schooler & Hertwig, 2005) it is assumed that if one of the two alternatives has a higher strength of association and is more fluently processed, then users will infer that this alternative has a higher value regarding to the criterion – in this case, the decision which wine region is more typical of Georgia. We assume that the decision in favor of one of the alternatives will be based on the higher individual strength of association for that alternative. This dependent variable was coded (-1) for the selection of "Kakheti" and (1) for the selection of "Imereti".

Another dependent variable was the recognition of tags. This measure was assessed in a multiple choice test consisting both of tags that were presented in the tag clouds (seven items) and tags which were not contained in the tag clouds (nine items). The task of the subjects was to correctly identify those tags which were presented in the tag clouds. The score was calculated as the sum of correctly identified items minus incorrectly marked items. Tags which were part of the manipulation ("Kakheti" and "Imereti") were not considered for the recognition score.

Results

To test the impact of individual and collective strength of association on the dependent variables, multiple regression analyses were conducted with the predictors individual strength of association, collective strength of association and the individual x collective strength of association interaction, and the dependent variables as criteria. The predictor variables were centered, and the interaction term was computed by a multiplication of both variables.

It was predicted that a higher individual strength of association would lead to a higher probability of selecting a tag corresponding to this association, whereas the contradicting collective strength of association is assumed to attenuate this tendency. To test these predictions, a regression with the criterion "Navigation Kakheti" was computed. The predictions were confirmed: the individual strength of association for "Kakheti" significantly increased the selection rate of the tag "Kakheti" (β = .34, p < .001), whereas the contradicting collective strength of association significantly decreased it (β = -.12, p < .01), adjusted R^2 = .12, $F(2, 528)$ = 38.50, p < .001. No significant interaction was found (β = .05, p = .21).

We also predicted that a higher collective strength of association would lead to a higher probability of selecting the corresponding tag, whereas a contradicting individual strength of association would lead to an opposite effect. To test these predictions, a regression with the criterion "Navigation Imereti" was computed. The predictions were confirmed: the collective strength of association for "Imereti" significantly increased the selection rate of the tag "Imereti" (β = .24, p < .001), whereas the contradicting individual strength of association significantly decreased it (β = -.08, p < .05), adjusted R^2 = .06, $F(2, 528)$ = 18.29, p < .001. No significant interaction was found (β = -.03, p = .56).

It was assumed that users would show incidental learning when navigating through tag clouds that represent collective strengths of associations. We predicted that users would change their individual strength of association and adapt to the collective strength of association. The strength of association for either "Kakheti" or "Imereti" was assessed in the dependent variable "decision". On the one hand, we assumed that a higher individual strength of association for "Kakheti" would also lead to a higher probability of choosing "Kakheti". On the other hand, we predicted that the collective strength of association for "Imereti" would increase the individual strength of association for "Imereti", leading to a higher probability of deciding in favor of this contradicting alternative. To test these predictions, a regression with the criterion "decision" was computed. Both predictions were confirmed: The strength of association for "Kakheti" significantly increased the tendency to choose this alternative (β = -.30, p < .001). The collective strength of association for "Imereti" significantly increased the tendency to decide in favor of the contradicting alternative "Imereti" (β = .24, p < .001), adjusted R^2 = .14, $F(2, 528)$ = 43.38, p < .001. No significant interaction was found (β = .01, p = .82).

Furthermore, we predicted an interaction between individual and collective strength of association for the dependent variables recognition and selection time: we assumed that for users with a high individual strength of association (e.g., for "Kakheti") a high contradicting collective strength of association (e.g., for "Imereti") would lead to a cognitive conflict, and that this conflict leads to a higher level of processing regarding all presented tags and to a longer duration of tag selection. To test the first of these predictions, a regression with the criterion recognition was computed. The prediction could not be confirmed: no significant interaction was found (β = .00, p = .95). What we did find, however, was that increasing individual strength of association significantly decreased performance in the recognition test (β = -.12, p < .01). The analyses did not reveal a significant effect for the collective strength of association (β = .03, p = .52), adjusted R^2 = .01, $F(2, 528)$ = 3.96, p < .05. To test the second of these predictions, a regression with the criterion selection time was computed. This prediction could not be confirmed: no significant interaction was found (β = -.01, p = .83). But the individual strength of association significantly decreased the time used for the selection process: a high individual strength of association led to a faster tag selection (β = -.16, p < .001). The analyses did not reveal a significant effect for the collective strength of association (β = .00, p = .96), adjusted R^2 = .02, $F(2, 519)$ = 6.51, p < .01.

Discussion

The aim of this study was to investigate the potential of emerging collective structures of the Web, such as social tags, on individual processes of navigation and learning. We addressed the research question how the collective externalized knowledge of a social tagging community could interact with individual knowledge, and if the navigation process per se – without the explicit intention to learn something – is sufficient for changing individual knowledge representations. In an experiment we investigated how the externalized representation of the associations of a community in a tag cloud affects the individual strength of association. Through the experimental manipulation we were able to create continuous levels for each of the two independent variables, the individual and collective strengths of associations.

The results showed that both the individual and the collective strength of association affect navigation. In the context of a Web search, these results suggest that, on the one hand, a user's prior knowledge is an important factor when choosing a navigation path. On the other hand, our results suggest that the collective knowledge of other Web users may help to open up better navigation paths, especially if a user's prior knowledge is deficient or biased. The results also show that users learn from the collective strengths of associations and, in the case of contradicting knowledge, that they will change their own individual strength of association by adapting it to the collective one. In this way, users will learn incidentally how a large community evaluates the relevance of certain information or concepts, and they can change their own strengths of associations accordingly.

Furthermore, the results revealed that a high individual strength of association leads to a faster and – as far as the perception of other available links is concerned – to a less thorough selection process. When a user has a strong, but incorrect strength of association, this could lead to a fast selection of a suboptimal navigation path. Especially in this unfavorable case social tags may be helpful: if the collective knowledge of a community was able to provoke a strong cognitive conflict, this could lead to a highly improved navigation process by that user. In this study, however, we could not find any interactions that suggest effects of cognitive conflicts caused by a highly contradicting individual and collective strength of association. A possible explanation could lie in the limitations of the scenario of this experiment, e.g. the rather static and simple navigation process, the small relevance of the task to the users, or the highly unfamiliar topic domain (which had only been selected for the purpose of manipulating the prior knowledge of users). So future research could focus on larger and more dynamic scenarios, combined with a variety of topic domains with a higher degree of relevance to the respective users. In addition, it would be interesting to create a setting which combines both tags as metadata and actual information resources or products.

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