The Role of Social Interaction Filter and Visualization in Casual Browsing

Indratmo
Grant MacEwan University
indratmo@macewan.ca

Julita Vassileva
University of Saskatchewan
jiv@cs.usask.ca

Abstract

Traces of social interaction in information spaces have the potential to improve information exploration. We evaluated interactive interfaces that utilize social interaction history. More specifically, we compared the value of a social filter and social interaction visualization in supporting casual browsing. We hypothesized that information filtering in general plays a more important role than visualization, as it provides additional control for users to browse information collections. Our experimental results showed that, compared to the baseline interface, the social filter increased subjective user satisfaction and was perceived by the study participants to enhance their effectiveness in finding interesting information. However, there were no significant differences between the social filter and social visualization systems. Our analysis suggested that the synergy of information filtering and visualization is more effective than each feature working separately.

1. Introduction

The Web has become a social information space. Web users interact not only with information items but also with other users through the commenting facilities in applications such as blogs, online newspapers, and social networking sites. This transformation has opened an opportunity to supplement content-oriented information exploration with social navigation. Our earlier study suggests that there is a high correlation between social interaction traces in a social web application and the degree of interestingness of information items [15]. Therefore, social interaction history in information spaces has the potential to help users find interesting information items.

Despite its potential, social interaction history has not been used widely to facilitate information exploration. Social measures such as the number of comments or commenters on information items can indicate the popularity of the items, but they are mostly unused by applications to support browsing. For example, when visiting a typical discussion forum, users do not have an option to filter messages by the number of replies. They have to rely on keyword search or browse the messages in a linear fashion.

In this study we provide an example of how developers can use social interaction history to facilitate information exploration. We enable users to interact with traces of social interaction in an information space through an information filter and visualization. Our main focus is on a casual browsing task where users do not have specific information needs but just want to find interesting information items or simply enjoy the exploratory activity [3, 33].

To compare the value of a social filter and visualization, we conducted a summative evaluation to measure the outcomes of casual browsing and subjective user satisfaction when people used three interactive interfaces for browsing social media datasets. This experiment was a follow-up to our previous study [14]. The main difference was that, in this experiment, we measured the effects of a social filter and visualization on the performance measures separately. In our previous study, the experimental design was influenced by Shneiderman’s mantra [25] and considered the social filter and visualization to be integral to the visualization tool. Consequently, we were unable to distinguish between the effects of the filter and visualization on the performance measures.

In our earlier analysis [14], we speculate that information filtering plays a more important role than information visualization, as a filter gives users additional control over their information spaces. However, we also note that both filtering and visualization contribute to the improved outcomes of casual browsing and user satisfaction with the browsing tool. Consequently, if these features are separated, each feature will become less effective for helping users explore an information collection.

Our experimental results showed that participants perceived the social filter to significantly enhance their effectiveness in finding interesting information, and were more satisfied with the interface providing the filter than the baseline interface. However, we did not find other significant effects of interface type on the performance measures, confirming our analysis that a separate filter and visualization is less effective than the synergy of both features.
2. Background and related work

2.1. Browsing

Browsing is an interactive information-seeking strategy that is usually unplanned, that relies on scanning and recognition of relevant information items, and that generally aims to explore and learn about the structure and content of an information space [2]. Compared to querying, browsing is often seen as an informal, heuristic, and opportunistic activity [23]. Browsing does not require searchers to specify their information needs explicitly as search terms. To initiate browsing, people need neither specific search goals nor formal search strategies such as looking up synonyms in advance to find appropriate search terms [2]. They may start with vague goals, which can be refined and narrowed down after they gain new knowledge and figure out what they want or need.

A browsing strategy has three main components: location, scan, and attention [26]. Location concerns the area of an information space that is viewed or explored. Movement from one location to another may refer to spatial movement (e.g., viewing a different area of a map) or semantic movement (e.g., viewing a different category of a collection). Scan refers to how users skim through information items in a location. Users may scan information items sequentially or even randomly; or they may use their knowledge of the domain to scan the items systematically. The last component, attention, concerns the selection of information items that are considered relevant and that should be examined more carefully.

Casual browsing is an exploratory task where users do not have real information need, but just want to find any interesting information items or simply enjoy the exploratory activity [3, 33]. The criteria of success are set by users themselves, and likely differ from one user to another. Unlike typical information retrieval tasks, casual browsing does not require users to find relevant items, as relevance is usually linked to information needs. Therefore, ‘interestingness’ instead of relevance becomes an important criterion to measure the outcome of casual browsing. These characteristics set apart casual browsing tasks from traditional information retrieval tasks and call for new evaluation methods.

2.2. Social interaction history

Social interaction history is built on the concept of computational wear or interaction history [13, 30]. The basic principle of computational wear is to record traces of interaction between users and digital objects (e.g., documents, spreadsheets, menus), construct a graphical representation of this interaction history, and then embed this visualization in the objects—resulting in history-rich objects [13]. Visualization of interaction history is analogous to use wear in physical objects.

Computational wear is motivated by observation that physical wear often conveys useful information [13]. For example, highlighted sentences in a book suggest ideas that are deemed important by the reader. Bear prints suggest the presence of bears in an area. Such interaction patterns are useful to help people make decision or adjust their actions (e.g., leaving an area immediately when seeing a lot of bear prints).

Unfortunately, interaction patterns that emerge naturally in the physical world are less visible in the digital world. Consider a typical file browser that displays files/documents in the same way. Looking at the file browser, users cannot differentiate frequently accessed files from those that are used rarely. Visualization of traces of interaction between users and digital objects can serve as information scent [24] that can facilitate users to assess the value of an information item and its relevance to their search goals.

Researchers have used interaction histories to enhance browsing and searching (e.g., 10, 18, 30, 31). Interaction histories vary from a simple list of recently visited websites to a complex aggregate of interaction traces left by many users. The main principle of these approaches is to monitor user activities in browsing and searching, and then use this data to facilitate search activity, such as providing suggestions to users who have similar information needs to those of other users in the past. A system may suggest relevant search terms to retrieve similar information items [10, 31], provide links to popular websites in which many users end up after submitting a query [31], or augment the user’s search history with meta-information such as the last access time to particular web resources or keywords used to find particular articles, and then allow the user to re-find these items using this local, contextual information [4, 18]. Such suggestions enable users to learn from past search trails (e.g., to see common terms used in a domain) and follow the trails of others if necessary.

Social interaction history extends the concept of computational wear by considering both user-object and user-user interactions that occur in an information space [15] (see Figure 1). The basic hypothesis is that social interaction traces imply the value of information items and can help users explore a collection. This hypothesis is derived from the concept of the wisdom of crowds [27]. If an item attracts attention from many people, this item must inherently contain some value (this value could be positive or negative).

The underlying reason why an information item becomes popular depends mainly on the context of a collection. Social interaction history may indicate the
degree of usefulness, interestingness, timeliness, novelty, or quality of an information item. For example, in a collection of academic papers, popularity may indicate the quality and impact of research in a particular field. In a movie collection, popularity may imply that a movie has a good story line and features good actors and actresses. In another case, a recipe may become popular because it is easy to follow and produces a healthy, delicious meal.

Besides the context of a collection, the characteristics of users also determine what social interaction traces imply. A community of serious scholars may appreciate thoughtful posts and dislike silly comments, whereas in another community, the sillier a comment is, the better the community will like it. People must be familiar with the characteristics of a collection and its users to understand the implied meaning of social interaction history.

Social interaction traces can facilitate social navigation and give users more control and flexibility in exploring information spaces. Simply stated, social navigation is an act of following other people [7, 9]. However, people have used this term broadly. Dieberger [6] uses social navigation to describe common practices such as asking other people for information, sharing interesting news with friends, and publishing a list of favorite websites on the Web. Konstan and Riedl [19] consider collaborative filtering to be another kind of social navigation. Collaborative filtering systems provide recommendations to users by comparing their profiles to other users’ profiles, and those who share similar profiles are recommended similar information items. An example of collaborative filtering can be seen at Amazon, which provides a list of recommended items based on its customers’ behavioral patterns (e.g., “Customers Who Bought This Item Also Bought…”).

In earlier work [16], we conducted an exploratory study to evaluate the feasibility of using social interaction history to improve browsing. We developed a tool for browsing a blog archive and gathered comments from our study participants. Most participants indicated that the social interaction visualization would allow them to identify popular blog entries quickly and effortlessly. However, it was unclear whether there was a real improvement in the outcomes of the browsing task. We followed up these initial results by conducting a summative evaluation and showed that visualization of social interaction history can help users find interesting articles, reduce wasted effort, and increase their satisfaction with the visualization tool [14]. In summary, our research attempts to enable social navigation by providing users an additional dimension of control – social dimension – to explore information spaces.

Our approach fits the transformation of the Web into a social information space. Recent applications such as Many Eyes [5, 29] and sense.us [12] enable collaborative data analysis by allowing users to create, share, and annotate visualizations of datasets. Users may highlight patterns on shared visualizations and leave comments on the visualizations. By reading comments from other users, one may find interesting patterns and their explanations which otherwise might be overlooked. To further support social navigation, graphical widgets have also been developed to reveal interaction traces in information spaces [32].

3. The experimental systems

To achieve the objective of this study, we compared and evaluated three interactive interfaces for browsing collections of Digg stories [8]. We used the Timeline visualization toolkit [28] to develop these interfaces. To avoid bias toward an interface, we used neutral names – Arjuna, Tambora, and Rinjani – to refer to these interfaces during data collection sessions.

3.1. Baseline (Arjuna)

The baseline interface arranges Digg stories along a timeline based on their submission times (see Figure 2). The interface consists of three panels. In the beginning the main panel shows and highlights the titles of stories in white, indicating that these stories have not been read by users. When users click on a title, the system removes this white background (i.e., read wear [13]) and displays the summary of the story in a popup window.

A summary consists of a story’s title, its number of diggs, comments, and commenters, its short description, and its submission time. Clicking on the title in this popup window takes users to the Digg website where they can read the contents of the story and comments on the story (if any) from the audience.
Below the main panel, there are two small panels that provide an overview of a collection. Ticks in these panels represent stories, and the light color background here indicates the currently visible time range. This overview is intended to help users know their current location and navigate the information space (e.g., move to another location that contains stories).

To facilitate information exploration, this interface enables users to pan across a timeline using a click-and-drag interaction technique. Users may click and drag either the main panel or the overview panels. They may also zoom in or zoom out on a particular area by scrolling their mouse wheel forward or backward respectively. Zooming in allows users to spread out stories along a more detailed timeline, reducing the number of visible stories in a view. Zooming out enables them to get an overview of a collection and move along the timeline quickly.

3.2. Social filter (Tambora)

The social filter is almost identical to the baseline interface (see Figure 3). All features of the baseline interface are also available in this interface. The difference between the two interfaces is that this interface provides a social filter that allows users to display only stories that have been commented on by a certain number of users. Filtering by the number of commenters on a story is a sample application of social interaction history. The numbers of commenters on stories are highly correlated to digg counts [15], which represent the degree of interestingness of Digg stories from a social perspective [22].

In this case, digg counts represent an explicit measure of interestingness, while the number of commenters an implicit one. Following the concept of dynamic query interfaces [1], we use a jQueryUI range slider [17] to implement this filter. Users filter out stories by dragging the left and right handles of this slider. For example, to remove stories with no commenters, users can drag the left handle a bit to the right to increase the low value of the range slider.

3.3. Social interaction visualization (Rinjani)

The social visualization system works in the same way as the baseline interface. The only additional feature of this system is that it visualizes the number of commenters on a story as a blue bar (see Figure 4). The lengths of these bars are proportional to the numbers of commenters on stories. This visualization provides a subtle cue for users to assess the relative popularity of a story in a collection from a social perspective. If users want to explore popular stories, they can look for stories with long bars. But if they want to find hidden gems, they can browse stories with no commenters.

4. Study methods

We aimed to compare the effects of a social filter and social interaction visualization on the outcomes of a casual browsing task and user satisfaction with the interfaces. We hypothesized that the filter overall offers more benefit than the visualization in facilitating casual browsing. We adapted the experimental design of our previous study [14], but applied different conditions. This study measured the effects of the social filter and visualization on browsing separately, whereas the previous study considered these features to be an integral part of the browsing tool.

We used a within-subjects design with one independent variable and five dependent variables. Interface type served as the independent variable and had three levels: baseline, social filter, and social visualization. We designed these interfaces to be similar to one another to isolate the main effects of the social filter and visualization on the performance measures. Thus, if there are significant differences between interfaces, we can attribute these differences to the presence or absence of a feature.

4.1. Participants

We recruited 15 participants (8 males, 7 females) to test the systems. Each participant received a $10 honorarium. Thirteen participants were between 20 to 29 years old, while two participants were between 30 to 39 years old. Participants consisted of mainly university students. On a scale of one (beginner) to nine (expert), participants self rated their computer skills as end-users at level three or above ($M = 6.27$, $SD = 1.67$). On a daily basis, ten participants spent 1–5 hours browsing the Internet, three spent 6–10 hours, and two spent more than 10 hours. Nine participants were familiar with Digg [8], while six others were not.

4.2. Setting and apparatus

All participants used the same equipment to perform the given tasks. The computer had Xeon 3.20 GHz dual processors with 1 GB of RAM running on Windows XP. The display was a 23-inch flat panel monitor with screen resolution set at 1920 by 1200 pixels. Participants used the Firefox web browser to explore three sets of Digg stories retrieved from the Educational, Travel & Places, and General Sciences categories. Each dataset consisted of 450 random Digg stories submitted between January 1, 2007 and
Figure 2. The baseline system visualizes a collection of Digg stories along a timeline

Figure 3. The social filter system provides an information filter to control visible stories

Figure 4. The social visualization system visualizes the number of commenters on each story
Table 1. Experimental matrix

<table>
<thead>
<tr>
<th>Participant Group Order</th>
<th>Educational</th>
<th>Travel &amp; Places</th>
<th>General Sciences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Arjuna</td>
<td>Tambora</td>
<td>Rinjani</td>
</tr>
<tr>
<td>2</td>
<td>Rinjani</td>
<td>Arjuna</td>
<td>Tambora</td>
</tr>
<tr>
<td>3</td>
<td>Tambora</td>
<td>Rinjani</td>
<td>Arjuna</td>
</tr>
</tbody>
</table>

December 31, 2009. Out of these stories, 20% received a popular status from Digg.

4.3. Performance measures

To evaluate the interfaces in supporting casual browsing, we used five dependent variables [14]:

- **Interest score** is a measure of the outcome of a casual browsing task and indicates how well users are able to find interesting articles. This score is assigned by participants to each article that they open during their browsing sessions (1: not interesting, 9: interesting).

- **Perception of support** is a measure of how well a system provides a good sense of support for users to find interesting articles. We adapted and used this questionnaire item [31]:
  
  Using this system enhances my effectiveness in finding interesting information.

  Strongly disagree 1 2 3 4 5 6 7 8 9 Strongly agree

- **User satisfaction** is a measure of how users like a system and is computed using these semantic differentials [20]:
  
  Terrible 1 2 3 4 5 6 7 8 9 Wonderful
  
  Difficult to use 1 2 3 4 5 6 7 8 9 Easy to use
  
  Dull 1 2 3 4 5 6 7 8 9 Stimulating
  
  Frustrating 1 2 3 4 5 6 7 8 9 Satisfying
  
  Overwhelming 1 2 3 4 5 6 7 8 9 Manageable
  
  Complex 1 2 3 4 5 6 7 8 9 Simple

- **Wasted effort** is the number of articles having an interest score three or below divided by the total number of articles opened during a browsing session (adopted from He et al. [11]). We assume that articles rated three or below to be uninteresting. Therefore, if users open such articles, then they waste some effort, as opening and reading an article takes more effort than just examining its summary.

- **Overall preference** is a measure of the overall functionality of a system.

4.4. Procedure

To avoid bias, we used a Latin square to counterbalance the order of system trials and datasets explored by participants (see Table 1) [21]. We then followed this procedure to run our experiment:

1. Explain the general objectives of the study and the consent process to the participant.
2. Ask the participant to fill out a pre-test questionnaire (demographic data).
3. Assign the participant to a system and a dataset according to the experimental matrix in Table 1, and describe the features of this system.
4. Give this scenario/task to the participant:
   
   You have a 15-minute free time period and want to spend the time for browsing articles about Educational/Travel & Places/General Sciences. You are not looking for specific information but just want to find interesting articles to read. Please browse the given collection using the system, and try to browse the collection in a natural way. You may skim through or read an article in detail. If you open an article, please submit your rating about the article.

5. Observe and take notes of how the participant uses the system to browse the dataset.
6. After 15 minutes, ask the participant to fill out a post-test questionnaire (perception of support and user satisfaction).
7. If the participant has not used all systems, then repeat steps 3 to 6. Otherwise, ask the participant to state his/her overall preference and the reasons.

5. Experimental results

Each data collection session took about one hour. After listening to a brief introduction to the experimental systems, all participants were able to use the systems without difficulties.

We ran one-way repeated measures analysis of variance (RM ANOVA) at the 0.05 level of significance to test mean differences among the interfaces. Mauchly’s test suggested that the experimental results met the assumption of sphericity. When RM ANOVA showed that there was a significant effect of interface type on a performance measure, we used Tukey’s Honestly Significant Difference (HSD) test to do post hoc pair wise comparisons between the means. Table 2 and Figures 5–7 provide a summary of the experimental results.

RM ANOVA showed that there was no significant effect of interface type on interest scores, $F(2, 28) = 2.37, p = 0.11$. These results implied that the degrees of interestingness of stories that users opened while using the interfaces were comparable.

There was a significant effect of interface type on perception of support, $F(2, 28) = 3.57, p = 0.04$. Tukey’s HSD revealed that participants perceived the social filter to significantly enhance their
effectiveness in finding interesting stories compared to the baseline ($p < 0.05$). The social filter increased the perception of support by 1.47 points compared to the baseline interface (29% improvement).

There was a significant effect of interface type on user satisfaction, $F(2, 28) = 4.14$, $p = 0.03$. Tukey’s HSD revealed that participants were significantly more satisfied with the social filter than the baseline ($p < 0.05$). The social filter increased the user satisfaction score by 0.76 points compared to the baseline interface (12% improvement).

There was no significant effect of interface type on wasted effort, $F(2, 28) = 2.12$, $p = 0.14$. These results suggested that the proportion of uninteresting stories to the total number of stories opened in a browsing session was not significantly different across the interfaces.

Regarding the overall preference, three participants preferred the baseline interface, nine the social filter, and three the social visualization. Despite the tendency to prefer the social filter, the chi-square test indicated that the user preferences did not deviate significantly from the expected distribution, $\chi^2 (2, N = 15) = 4.80$, $p = 0.09$. This test suggested that participants did not significantly prefer any particular interface.

### 6. Discussion

The experimental results showed that (1) there were significant improvements in perception of support and user satisfaction with the social filter compared to the baseline interface; (2) the social interaction visualization was not able to improve any performance measures significantly; and (3) there were no significant differences between the social filter and the social visualization.

Our initial goal was to tease apart the effect of social filter and visualization on a casual browsing task. While our results generally indicated that users performed best when using the interface supporting the social filter, there were no significant differences between the social filter and visualization. The small number of participants in our experiment might be the main reason why our statistical tests did not yield significant results. Further study with a larger sample size is needed to increase the power of the statistical tests and obtain more reliable results. Despite these limitations, we have taken various approaches to ensuring internal validity of our study. Below we analyze and compare the role of the social filter and visualization, and include comments (copyedited if necessary) from participants in our discussion. We also refer to our earlier work to compare the experimental results and provide more contextual information of the discussion.
6.1. Filter vs. visualization

The interfaces tested in our study were very similar, as we wanted to isolate the effects of the factors that were measured and compared – filter vs. visualization. All interfaces arranged information items in chronological order and allowed participants to pan across a timeline through a click-and-drag interaction technique. Therefore, there was no difference in how users moved from a location to another location.

The social filter and visualization affected how participants scanned a location and allocated their attention to particular items. The filter enabled users to reduce the number of visible stories in a location. Most participants used the filter to simply remove less popular stories from their views. A few participants utilized the filter as an exploratory tool: they typically started by exploring highly popular stories then less popular stories.

Regardless of how participants used the filter, it facilitated scanning by reducing the cognitive load of users, as they only needed to process fewer numbers of stories at a time and subsequently were able to pay their attention to stories of interest:

- The filter can help me to find some interesting stories.
- I like Tambora [social filter] because it is not overcrowded. I can select an article based on the popularity of the article.
- I liked Tambora because of the control or ability it gave to show or hide postings based on the number of commenters. … Tambora seemed less cluttered and I tended to look for keywords in titles.
- In my experience, there are a much higher number of articles to browse than I have time to look at. I enjoyed in the last system [social filter] how I could filter results by the number of commenters. I read through the most popular articles first, then, I set the filter to be less strict and I read the less popular articles next.

To some degree, the social interaction visualization had a similar role to that of the filter. It helped with scanning and allocating attention:

- The comment visualization helped draw attention to articles that were of interest to people.
- I tend to choose articles that have been read by many other readers. Presumably these articles are more interesting than those with less number of users or diggs. In this way, Rinjani [social visualization] is the best for me.

The social interaction visualization provided a subtle cue or information scent [24] that helped participants assess the potential value of an information item. This visualization enabled participants to notice popular stories easily and allocate their attention to these stories if they wish. The cue was available in a non-intrusive way, and participants had freedom whether or not to follow this social cue. Participants could still focus on the titles of stories to select those that interested them.

One of the disadvantages of providing the social filter alone was that users might ignore it. Although they knew about the filter, a few participants did not use it at all, and consequently did not receive the potential benefits of the filter. One considered that social interaction history was not very necessary and preferred “the cleanest and simplest interface” (the baseline interface). Another participant liked to pay attention to the titles and summaries of stories while browsing, and preferred the social visualization.

In contrast, it was hard, if not possible, to completely ignore the social visualization. Whether or not users were interested in using social navigation, the visualization always provided subtle information about the popularity of stories from a social perspective. Moreover, users did not have to do anything to benefit from this information. However, some participants perceived the visualization to be distracting rather than helpful, as it made the screen become overcrowded. Although users could alleviate this problem by having a zoomed-in view, participants underutilized the zooming feature of the systems while browsing.

Another limitation of separating the filter and visualization was that it was difficult to get a sense of popularity of visible stories, especially when the range of the filter was wide. Users might narrow down the range and adjust the filter repeatedly, but they might be reluctant to use this strategy, particularly when they did not have specific information needs.

In a previous study [14], we measured the combined effects of social filter and visualization on the outcomes of casual browsing and showed that they can help users find interesting articles, reduce wasted effort, and improve their satisfaction with the browsing tool. Compared to the current results, integrated social filter and visualization seem to be able to enhance each other’s strengths and alleviate the weaknesses. For example, the visualization can enhance the effectiveness of the filter because it provides a good sense of relative popularity of visible stories. Users can compare the relative popularity of stories by simply looking at the lengths of bars on visible stories. Without the visualization, they have to click on stories to retrieve this information. Some participants mentioned that the social interaction visualization made the screen overcrowded. Should they be able to use the filter to remove some stories, this problem would disappear or at least become less severe.
Overall, the results of this study were also in line with those of our exploratory study [16]. How users select stories to read are multidimensional involving content (e.g., titles) and popularity (e.g., number of commenters) of the stories. While a few participants preferred to focus only on the content dimension, most of them appreciated the ability to identify popular stories by using the social filter and visualization.

6.2. Lessons for developers

Information spaces may contain both explicit and implicit measures of the potential value of information items. On Digg, digg counts represent an explicit measure of the popularity of stories from a social perspective, as in general people “digg” a story if they find it interesting. However, not all applications have an explicit recommendation scheme. Fortunately, social interaction history usually contains rich information that can serve as implicit recommendation.

Choosing which implicit popularity measure to use must be done with caution. For example, click counts are not a good measure of the potential value of an article because the number does not tell whether users like or even read the article after clicking on it. The number of commenters may serve as a better indicator than the number of comments on an article. A few users may generate a high number of comments, for example, when they are involved in a flame war. However, when there are many users involved in a discussion, that discussion might contain valuable information, as people would spend effort contributing to a discussion only if they find the discussion useful or meaningful. Moreover, leaving a comment or contributing to a discussion requires more effort than just clicking on an article.

To deal with potentially misleading social indicators, developers can use multiple social measures. For example, instead of considering only the number of comments on an article, they should also consider other attributes such as click counts, the number of commenters, time of publication, the length of the article, the author, and so on. Qualitative aspects such as the reputation of the author or the commenters may improve the overall quality of the social indicators. For instance, an article commented on by a few prominent users might have higher quality than another article commented on by many unknown users. To come up with a “correct” formula requires a good understanding of the collection and its users.

To socially navigate an information space effectively, people do not need the exact value of a popularity measure on an information item (e.g., the number of diggs or commenters on a story). No participants seemed to care about the precise numbers of diggs, comments, or commenters on a story. They just needed to see which story was more or less popular than other stories. Thus, when using social interaction history to facilitate information navigation and exploration, developers must enable users to interact with social interaction history smoothly and effortlessly. For example, information filtering should not require users to enter the precise values of the desired range, but should use a dynamic query interface such as a range slider [1]. Social interaction visualization should be subtle, or provided as an optional feature, as this information is not the main focus of the user’s task. In the context of browsing, users typically focus on the content of information items to select which items to read (e.g., titles of stories or a list of keywords). Any use of social interaction history should not distract users from their main tasks.

7. Conclusion and future work

We compared and evaluated the value of a social filter and visualization in supporting casual browsing. Overall, participants perceived the social filter to enhance their effectiveness to find interesting information and had higher satisfaction with the social filter interface compared to the baseline interface. This study exemplifies an application of social interaction history to supplement content-oriented information exploration.

In future work, we are interested in exploring and identifying useful social indicators in information spaces. Which social indicators do affect users in selecting information items? How can we integrate multiple user activities (e.g., click counts, comment counts, commenter counts) into an effective formula that can help users find valuable items in a collection? In addition to quantitative measures, how can we use qualitative measures effectively (e.g., the reputation of users, the strength of relationships among users)? While our study participants were not part of Digg communities, Digg users (or members of a community) may have different preferences in selecting stories to read. In particular, they may consider stories posted or commented on by friends important, regardless of how other users think about the stories. We need further studies to examine these issues in order to use social interaction history effectively.

8. Acknowledgements

We have benefited from discussion with Melanie Tory and Carl Gutwin in designing our study methods. This research was funded by the Natural Sciences and Engineering Research Council of Canada Discovery Grants program.
10. References


