

Understanding and Controlling the Filter Bubble through Interactive Visualization: A User Study

Sayooran Nagulendra and Julita Vassileva

Department of Computer Science

University of Saskatchewan,

Saskatoon, Canada

{sayooran.nagulendra, julita.vassileva}@usask.ca

ABSTRACT

The “filter bubble” is a term which refers to people getting encapsulated in streams of data such as news or social network updates that are personalized to their interests. While people need protection from information overload and maybe prefer to see content they feel familiar or agree with, there is the danger that important issues that should be of concern for everyone will get filtered away and people will lack exposure to different views, living in “echo-chambers”, blissfully unaware of the reality. We have proposed a design of an interactive visualization, which provides the user of a social networking site with awareness of the personalization mechanism (the semantics and the source of the content that is filtered away), and with means to control the filtering mechanism. The visualization has been implemented in a peer-to-peer social network, called MADMICA, and we present here the results of a large scale lab study with 163 crowd-sourced participants. The results demonstrate that the visualization leads to increased users’ awareness of the filter bubble, understandability of the filtering mechanism and to a feeling of control over their data stream.

Categories and Subject Descriptors

D.2.8 [Information Storage and Retrieval]: Information Search and Retrieval – *information filtering*

General Terms

Design; Experimentation; Human Factors

Keywords

Visualization; Filter Bubble; Recommender Systems; Online Social Networks

1. INTRODUCTION

Today, social networks provide a global platform for people to share and collaborate with their friends and families. With the growth of mobile and web technologies, these social networks are growing rapidly and millions of users are sharing data with their friends and families. Facebook, Twitter and Google+ are currently the most widely used social networks. As of September 2013, Facebook has 1.15 billion users and 699 million daily active users

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

HT '14, September 01 - 04 2014, Santiago, Chile

Copyright 2014 ACM 978-1-4503-2954-5/14/09...\$15.00.

<http://dx.doi.org/10.1145/2631775.2631811>.

[1]. Nearly a quarter (24 %) of the content that is shared on the internet is shared on Facebook [2] and more than 3.5 billion pieces of content are shared each week [3], creating a stream of data that can overload any user. The social data overload problem is commonly solved by filtering out the irrelevant data. Personalized stream filtering mechanisms can reduce information overload by presenting the user with only the content deemed to be the most relevant. Some of the major social media sites, such as Facebook, Digg and YouTube, have already implemented personalized stream filtering.

Paradoxically, the main problem with information filtering algorithms is that they could be “too good”. The high level of optimization to the scope of interests of the user, inferred by these algorithms from the user’s previous behavior, leads to users becoming encapsulated in the “bubble” of their comfort, seeing only content related to their interests, and being spared of anything else. This is referred as “the filter bubble” problem [4].

We proposed an approach [5] to make the user aware of the filtering mechanism and take control over it. It is based on an interactive visualization that shows the filter bubble and some features of the hidden filtered data (its semantics and origin). The intention is to make the user aware of the user model that the recommender system has developed, so that the user can consciously decide to explore items that are filtered away by manipulating the visualization. Yet showing what is hidden and filtered away from the stream can bring back the social data overload problem. Therefore, the main challenge is to find an effective visualization technique that can be seamlessly integrated into the activity stream, and presents the right amount of detail about the hidden filtered social data, without contributing additionally to the social data overload.

In this paper we present a quantitative evaluation of an interactive visualization which metaphorically visualizes the filter bubble and provides awareness, understanding and control of personalized filtering to alleviate the filter bubble problem. The paper is organized as follows. Section 2 reviews related work on open learner modeling, explanation and visualization of recommendations, as well as on the filter bubble problem and some previous approaches to address it. Section 3 presents the visualization design, section 4 – a large study of the usability and understandability of the visualization using a crowd-sourced lab experiment. Section 4 discusses the results and Section 5 concludes the paper.

2. RELATED WORK

Recommender Systems (RSs) are software tools and techniques which adapt to the needs of an individual user and provide

personalized suggestions of the most relevant information [6]. The personalized suggestions help users to make decisions about consuming various types of items, such as what news items are interesting, what books to read or buy, what movie to watch and so on. Information filtering systems are a type of recommender systems, which select from a time-ordered stream of data (containing, for example, news, events, social updates, etc.) those that fit the scope of interest of the user. The difference between filtering and recommendation is that in filtering the irrelevant data is simply not displayed, i.e. remains hidden from the users, while in recommendation the most relevant data is highlighted in some way (e.g. shown first in a list of search results as in Google search, highlighted in a stream of data, etc.), but the irrelevant data is still available for the user to see.

Many researchers have worked on developing new RSs and improving the accuracy of their filtering algorithms. However the ultimate measure of success in this area is the user acceptance and trust of the recommendations [7]. The way recommendations are presented is critical for the user acceptance of recommender systems. Visualization techniques can be deployed to provide an intuitive “at a glance” explanation for recommendations and can also motivate the user to accept the recommendation. Presenting the recommendations in a ranked list according to their recommendation score is the most simple and commonly used visualization technique. Features like colour and font-size can be used to emphasize recommended items in a stream or list of items [8].

Previous work in the area of visualizing recommendations can be found in two communities – student modeling and recommender systems. In the AI and education / student modeling community, the idea dates back to the pioneering work by Kay and co-authors [9] on scrutable user models. Work by Bull et al. [10], Dimitrova [11], and Zapata-Rivera and Greer [12] on open learner modeling falls into this stream and more recently, work by Bakalov et al. [13]. More recently, Bakalov et al. [14], and Parra et al. [15] have expanded this work into the area of recommender system by visualizing user models and allowing users to manipulate them and control the system recommendation process.

A different stream of work on interactive visualizations of recommendations is motivated by the need to explain recommendations identified by Herlocker et al. [16] and elaborated by Tintarev & Masthoff [17]. An early attempt, by Webster & Vassileva [18] proposed an interactive visualization of a collaborative filtering recommender that allows the user viewer to see the other users in her “neighborhood”, who are similar to her, and also to change manually to degree of influence that any of the other users can have on the recommendations of the viewer. Much more elaborate approach of visualizing hybrid recommendation was proposed by Bostandjiev et al. [19].

Yet all these approaches focus on explaining to the user why she receives certain recommendations and on providing visual tools to change the recommendations. None of them shows the not-recommended items; they remain hidden. Two works take the approach of visually emphasizing items among all other non recommended items. iBlogViz [20] is a system that visualizes blog archives. It uses many visual cues to represent the blog content and social interaction history with the blog entry which help to navigate the blog archive quickly and easily. Particularly, visual cues about the social response (comments) to the news can be used to help users navigate stream data quickly to find interesting news. Rings (<http://rings.usask.ca>) [21] is a visualization of the Facebook social data stream, organized

around the people who post in the user’s Facebook stream. It helps the users of OSN to browse social data efficiently focusing on the active and influential friends and seeing the hidden time pattern of their social updates, without any filtering. In fact most of the users of Rings used the system to counter-act the Facebook filtering approach and to discover all the posts of their friends that they can’t normally see on their stream. This is an anecdotal evidence that some users in social networks realize that the social updates they see have been selected by Facebook, i.e. that they are in a “filter bubble” - a term introduced by Eli Pariser [4] to denote a limited scope of information defined by the user’s interests and isolated from anything that doesn’t belong to this scope.

Isolating the user in a filter bubble has its advantages and disadvantages. The main advantage is that it can help users get relevant information a lot faster while not causing social data overload. On the other hand, there are number of problems [4]. The first one is the problem of distortion of the content posted on the site or by the user’s friends and the user does not know in what way the way is biased. Users become less likely to be recommended information that is important, but not “likeable”. The second problem the filter bubble brings is the information equivalent of obesity. Because of the users’ tendency to give positive feedback, they will give feedback only to information items they are most compulsively attracted to. Using an analogy from food, users will be eating candy all the time, and the filter bubble leaves users locked in a world consisting of information junk food. As a result the users are increasingly surrounded by the ideas with which they are already familiar and agree, while being protected from surprising information, or information that challenges their views, makes them think or learn. Psychologist Lowenstein mentions that the “curiosity is aroused when we are presented with an ‘information gap’” and Pariser suggests that the existence of curiosity, is based on the awareness that something exists that is hidden or unknown [4]. The third problem is the matter of control, since the growth of user knowledge will be greatly influenced by the algorithms and systems giving excessive power to the computer scientists who develop the personalization techniques.

The importance of these three problems increases rapidly, as an increasing proportion of users are using OSN to get all their information and news; and nearly all OSN deploy information filtering to personalize their streams to users. Recommendation techniques have been applied to personalize the streams in online social networks such as Facebook, Google+ and Twitter [22, 23]. Facebook’s edge rank algorithm is one such filtering technique which presents a personalized stream of news and friends’ status updates to the user by ranking every interaction on the site [24]. Yet the algorithms used for filtering are not revealed by the companies and it is not possible to experiment with them or work to improve them. Moreover, most of the personalization systems do not create awareness about what is being hidden from the user.

Resnick et al. [25] outline some strategies for promoting diverse exposure. They discuss two approaches: the first one is to build diversity aware recommender systems and filtering mechanisms. As an example of this approach, Tandukar and Vassileva [26] developed an interest-based stream filtering technique, which allows for diversity exposure by allowing popular items to pass through the filter to ensure some serendipity. The second approach is to provide tools and techniques that encourage users to consider themselves searching for diverse exposure. Munson has implemented a browser extension which displays the bias in a

user's online news reading over time, which encourages users to seek the diverse exposure of news [27].

Though algorithmic personalization approaches can certainly find the most relevant content related to what users are already interested in a more efficient manner human curators and especially the user herself is probably the most appropriate agent to take the responsibility for ensuring a diverse exposure, to address the third problem outlined by Pariser. This means enabling the users to select what they want to see as well as what they do not want to see over the personalization presented by the algorithms. To enable them to do this, it is necessary first to make them aware of their filter bubble, as well as understanding of how they got inside it, and how they can control it to let different kind of information in and out, enlarge it or make it smaller. To our best knowledge there is currently no existing work that aims to create this kind of awareness and control in users. This is the aim of our work.

3. VISUALIZATION DESIGN

The first question when designing the visualization was to select a platform in which it would be possible to evaluate it. Currently, most of the popular OSN are centralized. Our previous experience with Rings [21] showed how difficult it is to do research on a live platform, which changes constantly the API and imposes access restrictions. Having no control or even detailed knowledge about the existing filtering mechanism makes it very hard to make convincing visualizations of the filtered data. That is why we decided to use our own OSN, called MADMICA [28] (available online at <http://madmica.usask.ca>), an implementation of a privacy-aware decentralized (peer-to-peer) OSN using the Friendica open source framework [29]. MADMICA uses a

personalized stream filtering mechanism, developed by Tandukar & Vassileva [30], which was developed and evaluated in a simulation [26]. This is a decentralized, content-based filtering algorithm, which enables each peer to learn the user's interests in discrete semantic categories, and to filter away messages received from the user's friends depending on the similarity of their interests. In essence, the filtering approach is based on a model of the user's interest in a finite set of categories of social data that is overlaid with a model of the strength of user interpersonal relationships (over each category). The intuition behind the filtering approach is that two people can be friends, but may not share the same level of interest in different topics or categories and may not trust each other's judgment or "likes" with regard to these categories.

The goals of the visualization are to create:

- 1) awareness,
- 2) understanding,
- 3) control of personalized stream filtering in an OSN to alleviate the filter bubble problem, and to
- 4) increase the users' trust in the system.

The visualization design is based on a bubble metaphor to make the effect of the personalized stream filtering in OSNs more understandable for the users (see Figure 1 and Figure 2).

It divides the space of the screen in two parts - outside and inside the bubble. The items that are inside the bubble are visible for the user, those outside the bubble are those that have been filtered away and are invisible in the stream (but they are shown in the visualization).

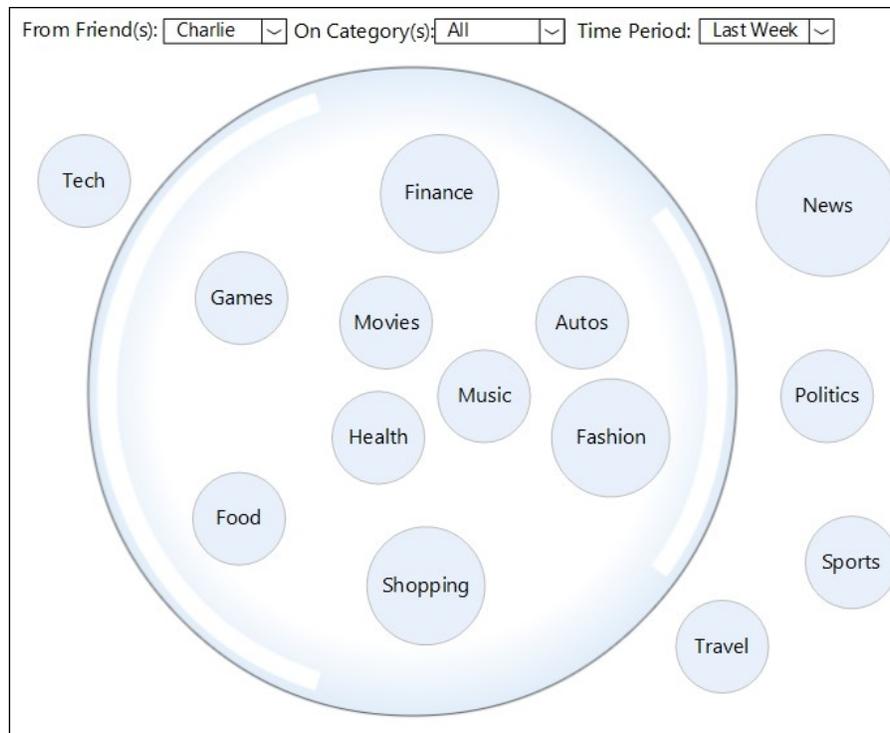


Figure 1. Anna's "category view" of her filter bubble related to Charlie's posts

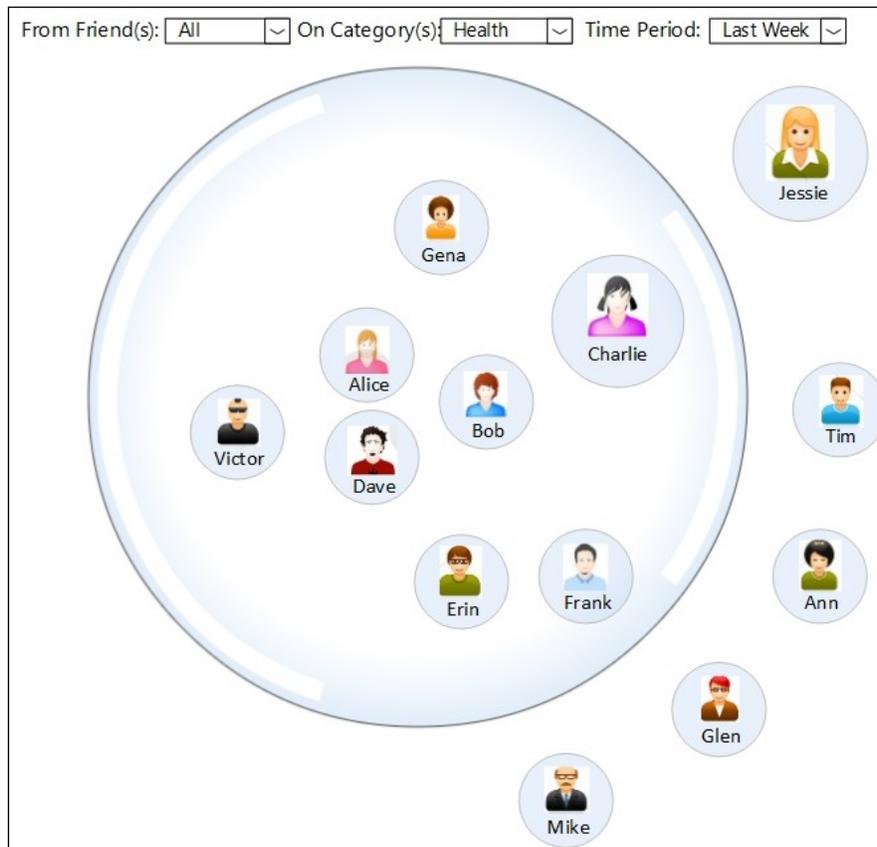


Figure 2. Anna's "friends view" of her filter bubble related to a certain category of posts ("health")

The visualization is personalized to the user viewing it (let's say Anna), and provides two alternative points of view: one focusing on the user's (Anna's) friends (see Figure 2) and one focusing on the semantic categories of the social data originating from them in the OSN (see Figure 1). We assume that there is a finite set of discrete semantic categories in which the content can be classified. For practical reasons, we consider categories of higher level of generality, e.g. "news", "technology", "health", "sport", similar to the categorization used by news websites, Google, Yahoo, etc., rather than user-generated tags, which can be too many, partially overlapping or redundant.

The category view shown in Figure 1 represents Anna's "Category view" - all the categories of the posts shared by Anna's friend Charlie during the last week that were shown in Anna's newsfeed (inside the bubble) or filtered out by the system (outside the bubble). All the category circles inside the bubble represent the categories of posts that are shown in Anna's newsfeed; they represent the categories of shared interests between Anna and her friend Charlie. But Charlie has more interests - those shown outside Anna's filter bubble. Anna is not interested in these categories or doesn't share Charlie's views, and therefore posts related to these categories are being filtered out by the filtering mechanism. The filtering mechanism decides which categories are of shared interest between Anna and Charlie based on the past history of actions that Anna performed on the posts shared by

Charlie in the category "health" (actions, such as "like", "share", "comment").

The "Friends view" of Anna's bubble visualization is shown in Figure 2. It represents all the friends who shared some posts in a given category (here, "health") during the last week that were shown in Anna's newsfeed or filtered out by the system. The position of each friend's circle relative to the big bubble is intended to create awareness about the filtering mechanism, i.e. whose posts related to the selected category, the user (Anna) can see in her newsfeed. For example, Anna receives all posts related to the category "health" from her friends Gena, Charlie, Alice, Bob, etc., but does not receive the health-related posts of Mike, Glen, Ann, Tim and Jessie. The filter bubble shape itself metaphorically creates the awareness that the user is encapsulated in a bubble and that there are friends outside of the bubble who have posted on the topic but the user has not seen these posts. Thus user awareness is achieved.

Providing some understanding about the personalized stream filtering is the second goal of this visualization. Organizing posts by categories and friends gives some understanding about the principles of the personalized filtering: that it is based on the categories of posts and the post origin (the friends who shared them). In addition to that, it visualizes the common interests between user and each of her friends - by selecting the "Category view" and a particular friend from the drop-down menu, the user

can see inside the big bubble are common interests between her and the selected friend. It also visualizes the interest-based communities of the user – by selecting the “Friend view” and a particular category of interest, the user can see in the big bubble all friends who share interest in this category with the user.

Providing control of the personalized stream filtering to the users i.e. allowing users to manually override the filtering system is the third main goal of this visualization. User control is achieved by allowing users to drag and drop the circles in and out of the big bubble in either of the two views. For example, if Anna drags and drops the circle representing the “games” category in the “Category view” (see in Figure 1) from inside the big bubble to its outside the user effectively tells the system that she does not like to see that category of posts from the selected friend in her newsfeed in the future. Similarly, the user could drag and drop a friend from within her “Friends view” bubble to the outside and it signals the system to filter out the posts shared by that friend about the selected category in the future. In the reverse situation, when the user realizes that she is interested in posts in category “health” shared by a friend (say, Glen), who is outside her “friends-view” bubble in Figure 2 and wants to see his posts in her newsfeed homepage in the future, she will drag and drop that particular friend inside the big bubble. Actually, this action is allows Anna to come out of her filter bubble and explore new interests. The visualization allows to apply the same action across all friends (in Category view) and across all categories (in the Friends view). For example, if Anna wants to see all posts by Glen in any category, she will select the “Friends view” and the generic category “All” from the “Categories” menu and then she will drag Glen in her bubble.

We presented in [5] a detailed justification of the visualization design decisions and a pilot user study to evaluate the usability and user acceptance of the visualization and whether it achieves its goals of providing awareness, control and trust in the filtering mechanism in MADMICA. Eleven (11) graduate students from the MADMUC research lab used the MADMICA system with the filter bubble visualization instead of Facebook and shared interesting and research-related links over a period of three weeks in March 2013. The results of the study showed that the filter bubble visualization made the users aware of the filtering mechanism, engaged them in actions to correct and change it, and as a result, increased the users’ trust in the system [5]. In order to gain a deeper understanding of the ways users perceive and understand the visualization, we carried out a large scale quantitative study with 163 Mechanical Turk participants, described in the next section.

4. EVALUATION

A quantitative study was carried out to evaluate the understandability of the visualization and whether the users understand that the visualization provides awareness, understanding and control of filtering and the filter bubble. The study was conducted as an online survey on a crowd-sourcing platform and required them to interact with the visualization, but not with MADMICA, as recruiting all participants to use our OSN would have been unrealistic.

4.1 Hypotheses

The goal of this user study was to find out if the visualization is understandable, if it creates awareness and understanding of the

personalized stream filtering mechanism and ability to control it to alleviate the filter bubble. So the evaluation aims at testing the following hypotheses.

1. Users understand that the visualization provides *awareness* of the filtering and the filter bubble.
2. Users understand that visualization provides *understanding* of the filtering and the filter bubble.
3. Users understand that visualization provides *control* of the filtering and the filter bubble.
4. Users understand the visualization and its functions.

4.2 Experimental Setup

The study was carried out as an online survey. Unlike the conventional online surveys, this survey had the interactive visualization embedded into the survey so that users could explore it and get some hands-on experience with it before answering the survey. First, the participants were given some introduction about the MADMICA social network and the filter bubble problem in general. Then a sample newsfeed homepage was displayed in the survey so that users could actually browse through the newsfeed without leaving the survey page. The sample newsfeed contained around 15 newsfeed items on 5 different categories such as Health, News, Movies, Music and Sports from five different hypothetical friends named Alice, Bob, Charlie, Dave and Frank. The participants were given instructions to assume that the aforementioned people are their friends in MADMICA and to browse through the newsfeed homepage as they would do in Facebook. In addition to this, 7 posts from different friends and in different categories were hidden from the newsfeed as a result of the personalization algorithm. Then the users were presented with the interactive visualization exactly as in the MADMICA system and were instructed to explore the visualization. Then they were directed to the questionnaire to answer the questions.

4.3 Method

The online survey was conducted using Amazon Mechanical Turk (MTurk) which is a popular crowd-sourced participant pool. We ensured the data quality by placing attention check questions (ACQs) and restricting participation to MTurk workers with certain qualifications [30].

The suggested qualification among researchers to ensure data quality was to allow participants who have the HIT Approval Rate (%) for all Requesters' HITs greater than or equal to 95 [30]. But we set even higher qualification to ensure the high data quality as follows: HIT Approval Rate (%) for all Requesters' HITs greater than or equal to 98% AND Number of HITs Approved greater than or equal to 5000. The data collection continued for 1 week and reached our target sample of 230 participants. Then we analyzed the data and checked the ACQ for validity and as a result, 163 valid responses were collected. For each participant with a valid response, we paid a compensation of 1\$, which is a good rate for an approximately 30-45 min. long study on MTurk.

The 25 questions were grouped according to the metrics which they intend to measure. The metrics for understandability of the visualization are adapted based on the International Standards for Software Quality Evaluation [31]. Table 2 summarizes the metrics chosen for the understandability of the visualization [31].

Table 2. Understandability Metrics

| Metric Name | Purpose | Formula | Interpretation of measured value |
|---------------------------------|--|--|---|
| Evident Functions | What proportions of functions users were able to identify by exploring the visualization | $X = A / B$ A = Number of functions identified by the user B = Total number of actual functions | $0 \leq X \leq 1$ The closer to 1.0 is the better. |
| Function understandability | What proportions of functions users were able to understand correctly by exploring the visualization | $X = A / B$ A= Number of functions whose purpose is correctly described by the user B= Number of functions available | $0 \leq X \leq 1$ The closer to 1.0 is the better. |
| Understandable input and output | Can users understand what is required as input data and what is provided as output by the visualization? | $X = A / B$ A= Number of input and output data items which user successfully understands B= Number of input and output data items available from the visualization | $0 \leq X \leq 1$ The closer to 1.0 is the better |

Table 3. Statistical Hypotheses

| Test | H0 (null) | H1 (alternative) |
|------|---|--|
| 1 | $\mu_{\text{Awareness}} \leq 0.5$ | $\mu_{\text{Awareness}} > 0.5$ |
| 2 | $\mu_{\text{Understanding}} \leq 0.5$ | $\mu_{\text{Understanding}} > 0.5$ |
| 3 | $\mu_{\text{Control}} \leq 0.5$ | $\mu_{\text{Control}} > 0.5$ |
| 4 | $\mu_{\text{Understandability}} \leq 0.5$ | $\mu_{\text{Understandability}} > 0.5$ |

Table 4. Hypothesis Analysis

| Test | Variable | Mean | 2-tailed t | Degree of freedom (df) | 1-tailed Critical t | 1-tailed t < 2-tailed t | Means are in correct order | Alternative Hypothesis Accepted |
|------|-------------------|-------|------------|------------------------|---------------------|-------------------------|----------------------------|---------------------------------|
| 1 | Awareness | .7117 | 11.358 | 162 | 1.6543 | YES | YES | YES |
| 2 | Understanding | .6176 | 6.953 | 162 | 1.6543 | YES | YES | YES |
| 3 | Control | .7607 | 14.824 | 162 | 1.6543 | YES | YES | YES |
| 4 | Understandability | .6967 | 13.884 | 162 | 1.6543 | YES | YES | YES |

There are 3 independent variables to assess the understandability of the visualization: awareness, understanding and control. Each of the independent variables was evaluated using the metrics given in Table 2 i.e. understandability of each independent variable was calculated. In addition to that, the overall understandability (referred as understandability hereafter) was also calculated using the understandability metrics. Six (6) questions (2 Yes/No and 4 Multiple Choice Questions) were used

to evaluate each of the independent variables. Altogether, 18 questions were used to evaluate the overall understandability with 6 questions for each metric. Our original hypotheses were converted into the statistical form with the corresponding null hypothesis (see Table 3).

As shown in Table 3, we considered the mean value of understandability for our hypothesis testing. The mean value is 0.5 according to the scale of metrics used to measure the understandability. We set the null hypothesis as the mean value of

understandability is less than or equal to 0.5, i.e. the participants do not have a clear understanding about the visualization. Our research hypothesis is the mean value is greater than 0.5, i.e. the participants do have clear understanding about the visualization. As mentioned in the metrics Table 2, the closer this mean value to 1.0 is, the better the understanding.

4.4 Results

The internal consistency (reliability) of question items was measured using the Cronbach's alpha. The acceptable value of Cronbach's Alpha should be the range of 0.70 to 0.95 [32]. The measured value for the Cronbach's alpha is 0.7 for our questionnaire. This value is in the acceptable range [33].

4.4.1 Test on the Four Hypotheses

One-sample t-test was used to determine whether the mean of a particular data set is different from the particular value. Before doing the t-tests, tests were carried out to verify that the following 4 conditions were met: understandability is measured at the ratio level, the collected data are independent which means that there is no relationship between the observations, there are no significant outliers in the data, and the understandability is approximately normally distributed [34, 35]. Then the t-tests were conducted for the 4 hypothesis tests and the results are summarized in Table 4.

The first t-test was conducted for the hypothesis 1 defined in section 4.2.1. The Mean understandability of awareness ($M = 0.7117$, $SD = 0.2379$) was higher than the tested understandability value of 0.5, a statistically significant mean difference of 0.21, 95% CI [0.18 to 0.25], $t(162) = 11.358$, $p < .001$.

Similarly, the t-tests for hypothesis 2, 3, 4 were conducted and the results follow. The Mean understandability of *understanding* the filtering ($M = 0.6176$, $SD = 0.2159$) was higher than the tested understandability value of 0.5, a statistically significant mean difference of 0.12, 95% CI [0.08 to 0.15], $t(162) = 6.953$, $p < .001$. The Mean understandability of *control* ($M = 0.7607$, $SD = 0.2246$) was higher than the tested understandability value of 0.5, a statistically significant mean difference of 0.26, 95% CI [0.23 to 0.30], $t(162) = 14.824$, $p < .001$.

Finally, the Mean *understandability of visualization* ($M = 0.6967$, $SD = 0.1808$) was higher than the tested understandability value of 0.5, a statistically significant mean difference of 0.20, 95% CI [0.17 to 0.23], $t(162) = 13.884$, $p < .001$. In all four tests, there were a statistically significant difference between means ($p < .001$) and, therefore, we can reject the null hypotheses defined in Table 3, and accept the alternative hypotheses.

4.4.2 Additional Test on Graphical Language

The key graphical language constructs of this visualization are:

1. The relative position of user's circles to the bubble (inside / outside)
2. The size of the users' circles (larger - more posts)
3. Dragging user circles in and out (showing / filtering away)

In addition to the above 3 constructs, we identified another potential construct from the qualitative study as follows: the relative position of circles inside the bubble (closer to the center or to the periphery). All the 3 other constructs were as part of each function of the visualization (providing awareness, providing understanding, and providing control) and were tested for statistical significance. In order to test whether users interpret this fourth construct or not, we included the answers based on this

construct for two of the questions in the survey. During the analysis, we created a score for users based on how many out of the 2 questions they did not select this construct as an answer. Then the hypotheses were formed as follows: $H_0: \mu_{\text{Score}} \leq 0.5$, $H_1: \mu_{\text{Score}} > 0.5$. One sample t-test was conducted and the results are as follows: the Mean score for not selecting the graphical construct ($M = 0.9571$, $SD = 0.1405$) was much higher than the test score value of 0.5, a statistically significant mean difference of 0.46, 95% CI [0.44 to 0.49], $t(162) = 41.523$, $p < .001$. There were a statistically significant difference between means ($p < .001$) and, therefore, we can reject the null hypothesis, and accept the alternative hypothesis.

4.4.3 Discussion

The results of the study suggest that overall the participants had a good understanding about the visualization. By comparing the means of variables Awareness, Understanding, and Control, we can see that users have a good understanding (0.7607) about the control of filtering and the filter bubble provided by the visualization. This can be linked with the drag and drop feature of the visualization, which is very popular and commonly used action in many user interfaces. On the other side, the users' understanding about the visualization providing understanding to the filtering and the filter bubble has the lower value (0.6176). Though it is higher than 0.5, it clearly shows that the visualization has to be improved on this aspect. A possible improvement could be to provide some context sensitive help to the visual cues in the visualization. The overall understandability value of the visualization (0.6967) shows that the users had good understanding about the visualization after exploring it for a short time and it could be considered as an intuitive visualization. But it can be envisioned that the users will better understand if there is a context sensitive help provided with the visualization.

Analyzing the t-test values gives us more insight into the understandability measures. As mentioned earlier, the understandability of visualization is calculated using the three variables awareness, understanding and control. These three variables are understandability variables and are measured using the metrics presented in Table 2. The variables awareness, understanding and control obtained a high 2-tailed value respectively 11.358, 6.953, and 14.824. These values are comparatively very high when compared with their relevant one-tailed t-test value, which is 1.65. This indicates that these three variables are a very good measure for the understandability of this visualization.

The additional test on graphical language results suggest that the users very rarely interpreted the position of circles inside the bubble (closer to the center or to the periphery). A possible reason for this might be the nature of the question; the users might have only focused on the first 3 graphical constructs which are intuitive and obvious. Yet, the position of circles inside the bubble seems a useful construct and could be added as an improvement to the visualization in future.

5. CONCLUSIONS

This paper presented an interactive visualization of the information filter bubble that can help users understand how information filtering works in an online social network, and empowers them to control the algorithms by manipulating the visualization to "escape" the bubble. This is a novel contribution since no previously existing approaches to visualizing

recommendations have focused specifically on the filter bubble problem. The results of a crowd sourced lab study with 163 participants demonstrates that the visualization leads to increased users' awareness of the filter bubble, understandability of the filtering mechanism and to a feeling of control over the data stream they are seeing. Future work directions include conducting a study of evaluating the intuitiveness of the visualization by comparing it to the same interactive visualization provided with guided help.

6. ACKNOWLEDGEMENT

This work has been supported by the NSERC Discovery Grant of the second author.

7. REFERENCES

- [1] Facebook Investors, Available online at: <http://investor.fb.com/releasedetail.cfm?ReleaseID=780093>. (accessed 4 Aug 2013)
- [2] Chart of the day: How People Share Content on the Web, Available online at: <http://www.businessinsider.com/chart-of-the-day-social-networking-sites-dominate-sharing-2009-7>. (accessed 4 Aug 2013)
- [3] An Infographic: The Biggest Shift since the Industrial Revolution | TechnoBuffalo, Available online at: <http://www.technobuffalo.com/2010/06/01/an-infographic-the-biggest-shift-since-the-industrial-revolution/>. (accessed 5 Sept 2013)
- [4] Pariser, E.: *The Filter Bubble: What the Internet Is Hiding from You*. Penguin Press HC (2011)
- [5] Nagulendra, S., Vassileva, J.: Providing Awareness, Understanding and Control of Personalized Stream Filtering in a P2P Social Network. 19th International Conference, CRIWG 2013. pp. 61–76 Springer Berlin Heidelberg (2013).
- [6] Resnick, P., Varian, H.R.: Recommender systems. *Communications of the ACM*. 40, 3, 56–58 (1997)
- [7] Konstan, J.A., Riedl, J.: Recommender systems: from algorithms to user experience. *User Modeling and User-Adapted Interaction*. 22, 1-2, 101–123 (2012)
- [8] Webster, A., Vassileva, J.: Visualizing personal relations in online communities. *Proceedings of the adaptive hypermedia and adaptive web-based systems (AH'2006)*, June 21–23, pp. 223–233, Springer LNCS 4018, Dublin (2006)
- [9] Cook, R., and Kay, J. The Justified User Model: A Viewable, Explained User Model. In *Proc. of the 4th Int. Conf. on User Modeling* (1994)
- [10] Bull, S., Pain, H. & Brna, P. (1995). Mr. Collins: A Collaboratively Constructed, Inspectable Student Model for Intelligent Computer Assisted Language Learning, *Instructional Science* 23(1-3), 65-87.
- [11] Dimitrova, V.: STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education* 17(2), 35–78 (2003)
- [12] Zapata-Rivera, J. D., & Greer, J. (2004) Interacting with Bayesian student models. *International Journal of Artificial Intelligence in Education*. 14(2), 127-163.
- [13] Bakalov F., König-Ries B., Nauerz A., and Welsch M: IntrospectiveViews: An Interface for Scrutinizing Semantic User Models. *UMAP 2010*: 219-230.
- [14] Bakalov F., Meurs M.-J., König-Ries B., Sateli B., Witte R., Butler B., Tsang A.: An approach to controlling user models and personalization effects in recommender systems. *IUI 2013*: 49-56
- [15] Parra D., Brusilovsky P., Trattner Ch.: See what you want to see: visual user-driven approach for hybrid recommendation. *IUI 2014*: 235-240
- [16] Herlocker J. L., Konstan J. A., and Riedl J.: Explaining collaborative filtering recommendations. In *Proceedings of ACM CSCW'00 Conference on Computer-Supported Cooperative Work*, 2000.
- [17] Tintarev N. and Masthoff J.: A survey of explanations in recommender systems. In *Data Engineering Workshop, IEEE 23rd International Conference*, 801–810, 2007.
- [18] Webster, A., Vassileva, J.: The KeepUP Recommender System. *Proc. 2007 ACM Conference on Recommender Systems RecSys '07*. pp. 173–176 ACM, Minneapolis, Minnesota, USA. (2007)
- [19] Bostandjiev S., O'Donovan J., and Höllerer T.: TasteWeights: A Visual Interactive Hybrid Recommender System. In *ACM Recommender Systems: 2012*
- [20] Indratmo, Vassileva, J., Gutwin, C.: Exploring blog archives with interactive visualization. In: *International conference on Advanced Visual Interfaces* (2008)
- [21] Shi, S.: Keeping Up with the Information Glut by Visualizing Patterns of Posting by Friends on Facebook, <http://hdl.handle.net/10388/ETD-2011-09-139>, (accessed 11 Feb 2013)
- [22] Kywe, S.M. et al.: A Survey of Recommender Systems in Twitter. *Proc. 4th International Conference, SocInfo 2012*, Lausanne, Switzerland, December 5-7, 2012. pp. 420–433 (2012)
- [23] Manish, A. et al.: An Online News Recommender System for Social Networks. *SIGIR-SSM*. (2009)
- [24] Kincaid, J.: EdgeRank: The Secret Sauce That Makes Facebook's News Feed Tick | TechCrunch, Available online at: <http://techcrunch.com/2010/04/22/facebook-edgerank/>. (accessed 6 July 2013)
- [25] Resnick, P., A. Munson, S., Garrett, R.K., Stroud, N.J., Kriplean, T.: Bursting Your (Filter) Bubble: Strategies for Promoting Diverse Exposure. *Proc. Conference on Computer supported Cooperative Work CSCW 2013 Companion proc*. pp. 95–100 ACM (2013)
- [26] Tandukar U., Vassileva J.: Ensuring Relevant and Serendipitous Information Flow in Decentralized Online Social Network. *Proc. AIMSA'2012*, 15th biennial conference on AI Methods Systems, Applications, Springer Verlag, LNAI 7557, pp. 79-88. (2012)
- [27] Munson, S.A., Resnick, P.: Presenting diverse political opinions. *Proc. 28th international conference on Human factors in computing systems - CHI '10*. p. 1457 ACM Press, New York, New York, USA (2010)
- [28] Nagulendra, S., Vassileva, J.: Minimizing Social Data Overload through Interest- Based Stream Filtering in a P2P Social Network, *Proc. IEEE International Conference on Social Computing, SocialCom'2013* (2013)
- [29] Macgirvin, M.: DFRN – the Distributed Friends & Relations Network, Available online at: <https://macgirvin.com/spec/dfrn2.pdf>. (accessed 2 Aug 2012)

[30] Paolacci, G., Chandler, J.: Running experiments on Amazon Mechanical Turk. *5*, 5, 1–14 (2014).

[30] Tandukar, U., Vassileva, J.: Selective Propagation of Social Data in Decentralized Online Social Network. Proc. UMAP 2011 Workshops, LNCS 7138. pp. 213–224 Springer-Verlag Berlin Heidelberg (2012)

[31] ISO/IEC TR 9126-2:2003 – Product Quality – External Metrics, Available online at: http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=22750. (accessed 2 Feb 2014)

[32] Bland, J. M., Altman, D. G.: "Statistics notes: Cronbach's alpha," pp. 570-572 (1997)

[33] George, D., Mallery, P., SPSS for Windows step by step: A simple guide and reference. 11.0 update (4th ed.), Boston: Allyn & Bacon (2003)

[34] Testing for Normality using SPSS, Available online at: <https://statistics.laerd.com/spss-tutorials/testing-for-normality-using-spss-statistics.php>. (Accessed 2 Mar 2014)

[35] One-Sample T-Test using SPSS, Available online at: <https://statistics.laerd.com/spss-tutorials/one-sample-t-test-using-spss-statistics.php>. (Accessed 2 Mar 2014)