

Increasing Engagement through Early Recommender Intervention

Jill Freyne*, Michal Jacovi**, Ido Guy**, Werner Geyer***

*Clarity Research Center
University College Dublin
Belfield, Dublin 4,
Ireland
jill.freyne@csiro.au

**IBM Haifa Research Lab
Mt. Carmel
Haifa – 31905,
Israel
{jacovi, ido}@il.ibm.com

***IBM T.J Watson Research
One Rogers Street
Cambridge, MA 02116, USA
werner.geyer@us.ibm.com

ABSTRACT

Social network sites rely on the contributions of their members to create a lively and enjoyable space. Recent research has focused on using personalization and recommender technologies to encourage participation of existing members. In this work we present an early-intervention approach to encouraging participation and engagement, which makes recommendations to new users during their sign-up process. Our recommender system exploits external social media to produce people and profile entry recommendations for new users. We present results of a live user study, showing that users who received recommendations at sign-up created more social connections, contributed more content, and were on the whole more engaged with the system, contributing more without prompt and returning more often. We further show that recommendations for multiple content types yield significantly better results, in terms of user contribution and consumption; and that recommendations of more active users yield a higher return rate.

Categories and Subject Descriptors

H.5.3 [Group and Organization Interfaces]: Web-based interaction, H.5.3 [Group and Organization Interfaces]: Collaborative computing

General Terms

Measurement, Experimentation, Human Factors

Keywords

Social networking, social software, adoption, recommender systems, participation, community, Web 2.0

1. INTRODUCTION

Social media sites have gained huge popularity in recent years, attracting millions of visitors who contribute and consume content. These sites rely primarily on the actions and contribution of their users to create a rich, lively, useful, and

enjoyable space which draws people back again and again. Consider Wikipedia without authors, YouTube without contributed videos, delicious without tagged pages, and finally Facebook or MySpace without profiles and posts.

The key motivations for participating in social media stem from a sense of belonging and influence. These contribute to the “stickiness” of a social Web site [20]. Being part of a community of users provides participants with a few key senses: (1) efficacy - a sense that they are part of a community and have an effect on an environment or an impact on a group; (2) anticipated reciprocity whereby users contribute if they believe that they will benefit in return; and finally (3) increased reputation and recognition online and amongst friends [8].

Social network sites (SNSs) provide users with facilities allowing the fulfillment of all of the motivations for participating in social software. If users can identify people with whom they are familiar, they can achieve a sense of closeness within a small group and overall within the large community. By contributing content, which receives views and comments, users feel that they have made valuable contributions to others. SNSs, despite their popularity, are not immune to the problems of adoption faced by many types of social software. Consider, for example, the membership figures provided for Facebook; comScore reports that 220 million unique users visited Facebook in December 2008 [4], however Facebook itself reports only 150 million active users as of January 2009 [9]. This shows that at least 70 million (~31%) of Facebook’s December visitors failed to remain active. The problem illustrated by this example can be described as a “stickiness” problem where a percentage of users fail to get hooked or “stuck” on a system and cease to use it. All social media sites suffer from this problem to some degree.

When users sign up to a SNS, they often spend their first few visits creating an online profile and seeking out others whom they know in order to form social connections. Users who fail to locate familiar people may feel alone on the site and fail to see its benefit. We believe that the cornerstone of successful interaction in this social medium is to acquire a critical mass of users [17] and to make new members aware of relevant users early in their membership, in order to increase the sense of community belonging. Encouraging users to provide profile information is another stumbling block for SNSs. Contributing profile content allows users to create a digital representation of their choice for others to consume. The content itself acts as a platform for communication and interaction in the form of tagging, commenting, and so on. A poorly populated profile might suggest an inactive user, often discouraging others from

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. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

RecSys’09, October 23–25, 2009, New York, New York, USA.
Copyright 2009 ACM 978-1-60558-435-5/09/10 ...\$10.00.

returning to view content and to initiate communication. These forms of interaction are vital in the sustainability of the system.

In order to alleviate the problems highlighted above, we propose an intervention aimed at encouraging participation and engagement within an existing SNS, Beehive, to see how it affects both the early activity levels and contributions of users, and the long term “stickiness” of the site. Specifically, we propose the use of recommender technology to suggest people to connect to and content to contribute (or both) during sign-up.

Our people recommender technique exploits the social information aggregator SONAR [12] to make friend recommendations and allows a one-click-connects-many operation to simplify and expedite the friend making process. Our content creation recommender suggests About You topics (free-form textual entries which provide users with a casual way to describe themselves or their opinion) that the user can fill in [7]. We expect that the direct effect of our recommender would be to lead to more representative user profiles, in terms of both articulated connections and user contributed content. However, we also hypothesize that our recommendation strategy will have indirect effects on the engagement levels of users across the site and the overall “stickiness” of the system. We believe that users who are immersed into a ready-made community will have increased levels of exploration and contribution and will return to the site more often.

As mentioned, the system examined in this work is Beehive, an enterprise social network site developed and deployed within IBM. The system has over 50,000 registered users and like many social media systems, it has its share of users who fail to return. An analysis of the 50,000 users showed that 34% were active for less than 48 hours and a further 16% were active for less than one month.

We present empirical results of an extensive user study that includes over 1,000 users of Beehive. Our two main contributions are: (1) suggesting a novel approach for making effective recommendations to newcomers, handling the new user problem by leveraging aggregated external data from other social media sites; and (2) showing that in terms of engagement with a social website (consuming and producing more content) recommendations of more than one type of content, specifically of people to connect to and content to create, are most effective; and in terms of return rates, being introduced to highly active users results in a higher return rate.

The remainder of the paper is structured as follows. In the next section we examine related work. Section 3 provides details of the technology used and the recommendation processes we implemented. Section 4 details the evaluation and empirical results. Section 5 concludes and suggests future work.

2. RELATED WORK

Recommender systems are increasingly becoming an important part of social media sites in order to attract new users as well as retain existing ones, by highlighting artifacts such as books, movies, pictures, or blogs that may be of particular interest to users. *Collaborative filtering* [15] has become a popular method for providing recommendations based on similarity between users, reflected by their preferences. Typically, similarity is determined based on some explicit feedback (such as item rating) or implicit feedback (such as item selection) that users provide. In this work, we use familiarity relationships,

determined by mining social media interaction information, rather than similarity between users, for recommendations.

Previous work has leveraged articulated social network structures for recommendations. For example, Bonhard et al. [1] explore various methods for the production of movie recommendations and find that users prefer recommendations from familiar people. Similarly, Sinha and Swearingen [19] show that users prefer recommendations from their friends rather than from online systems. Other research has been conducted to explore recommendations of groups or content within a SNS environment. Spertus et al. [21] recommend online communities to members of the Orkut SNS. Groh and Ehmig [11] show that collaborative filtering can be improved by harnessing articulated network relationships. Geyer et al. [10] discuss recommendations for content contribution within an enterprise SNS and show not only a significant increase in entries and users with entries, but also that articulated social networks can be effectively harnessed to create recommendations. In all these works, recommendations are provided for established users and are based on the SNS’s articulated network.

Work which aims at directly encouraging adoption and participation includes incentive mechanisms and measures which strengthen the sense of community belonging. Harper et al. [14] explore personalized invitations, a particular type of designed incentives, as means for increasing participation in an online discussion forum. They find that invitations, in particular those emphasizing the social nature of the forum, have an immediate impact over the short term, causing users to write and view more posts. Farzan et al. [8] employ a point-based incentive system within an enterprise SNS. Employees are found to be initially motivated to add new content to the site due to both points and status levels supported by the system. Sun and Vassileva [23] show that a motivational social visualization within an online community effectively increases community awareness and social comparison. As a result, the number of multiple forms of content contributions goes up significantly.

The scarcity of information relating to new users makes it very difficult to produce accurate personalized recommendations. This is known as the *New User* or *Cold Start Problem*. Rashid et al. [18] suggest different techniques that collaborative filtering systems can use to learn about new users. These techniques try to guess what items a new user is likely to be able to rate. Kohrs and Merialdo [16] also propose algorithms for the selection of objects to be rated by new users for a more efficient training of collaborative filtering systems. Drenner et al. [6] require that new users of MovieLens will not only rate, but also tag movies during the sign-up process. They show that this results in a huge increase in the number of tags entered to the system with a relatively small increase in user attrition. They also observe that users who are required to tag in the initial process are significantly more likely to tag in subsequent visits.

Previous research has been carried out on recommendation algorithms suitable to make additional friends in SNSs. Chen et al. [3] compare various algorithms for recommending people in an enterprise SNS. They examine recommendations for people with whom the user is familiar as well as people who are unknown, but may be of interest to the user. Guy et al. [13] introduce a widget that recommends possible connections to existing users within an enterprise SNS, using a similar method to the one used in this work. The people recommendations in the

mentioned research have been applied to existing users within a SNS, while we target recommendations at new users.

Burke et al. [2] study newcomers to Facebook in order to predict long-term sharing based on the experiences users have in their first two weeks. While not employing any active encouragement on users, they show that mechanisms such as learning from friends, and feedback, have a positive effect on users' later engagement on the site. Encouraged by this finding, we present users with recommendations that can speed their friending, to improve their learning from friends; and encourage them to contribute content, to increase their chances for feedback.

3. SYSTEM OVERVIEW AND RECOMMENDATION FEATURES

Beehive is an enterprise social network site within IBM. It was officially launched in September 2007 and had more than 50,000 users at the time of the study. Similarly to other SNSs, Beehive includes an individual profile page for each user, and supports features like connecting to others, setting status messages, sharing photos, lists, events, and commenting on users and content. Beehive has experienced viral adoption since its launch and users share a wealth of personal and professional information on the site [5].

Profiles in Beehive include user-created content, the user's social network ("friends"), comments, and user activity. The user-created content includes freeform question and answer pairs (About You entries) that allow users to select and present personal information, opinions and work-related information in a friendly manner. The entries take the form of a question or title followed by a response. While many of the About You entries were questions, others had more topical titles, such as "Favorite Book". Profile About You entries play an important role in creating an online identity and help form personality impressions [22]. The novelty of the About You format is that the questions are not defined by the system, users can copy from others or create their own questions. Figure 1 shows a sample user's About You's. Previous research [7] has shown that diversity of such entries in profiles is associated with a higher number of friends.

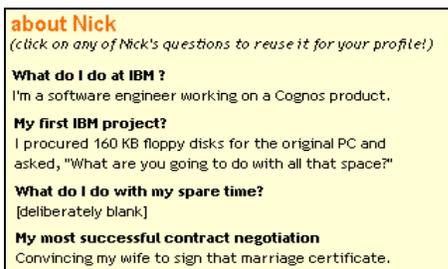


Figure 1 Sample users' About You entries

3.2 SONAR

SONAR is an information aggregation system, which gathers social network information from different public data sources within an enterprise [12], [13]. In this work, SONAR was configured to aggregate information from the following seven data sources within an Intranet: organizational chart, publication

database, patent database, friending system¹, people tagging system, project wiki, and blogging system. From each of these data sources SONAR extracts explicit relationships, social connections, or direct interactions (e.g. co-authored a paper together or commented on each others' blogs), and computes a normalized score in the range of [0,1] for each relationship between two people whenever corresponding data is available, where 0 indicates no relationship and 1 indicates the strongest relationship. Each source is given equal weight and these scores are aggregated to a unified single score in the range of [0,1]. Given a user, the SONAR API returns a list of related users and their aggregated familiarity score. The SONAR API also provides an explanation of the score. For example, an explanation could be "You have co-authored 3 papers". More details on SONAR can be found in [12].

3.3 Sign-up Recommendations in Beehive

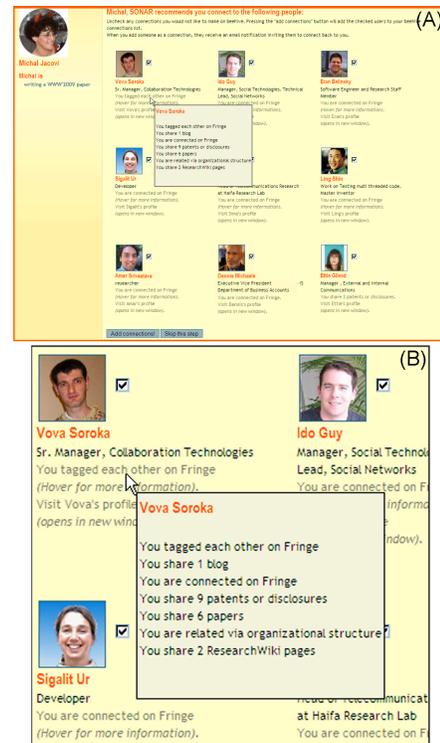


Figure 2. People recommendation page

In order to encourage engagement and increase the adoption of the Beehive sign-up process, we added recommender elements to the Beehive sign-up process. As previously mentioned, the new user problem refers to the inability of recommender systems to make recommendations for new users due to a lack of relevant information. Beehive suffers from this problem and although recommendations have been investigated on the site [3] [10], most of those techniques could not be applied to new users. SONAR, however, provides the facility to identify a set of recommendation candidates for each new user based on data sources external to Beehive. Using SONAR for people

¹ SONAR can manage data from multiple friending systems.

recommendations during sign-up encourages users to seed their friendships at a very early stage and provides the system with an articulated network on which further recommendations can be made, in our case About You entries.

The first type of sign-up recommendation presents up to nine people that the new user should connect to (see Figure 2). Each recommendation includes a thumbnail image of the recommended person; the image is decorated with the name and job role of the person, as well as evidence to the relationship with the user. By showing users familiar faces, the recommender aims to increase users' sense of community belonging immediately. The underlying assumption is that if users realize that their friends are present on the site, they are more likely to stay. If friends respond with feedback, this is further likely to increase the sense of community belonging at an early stage [2].

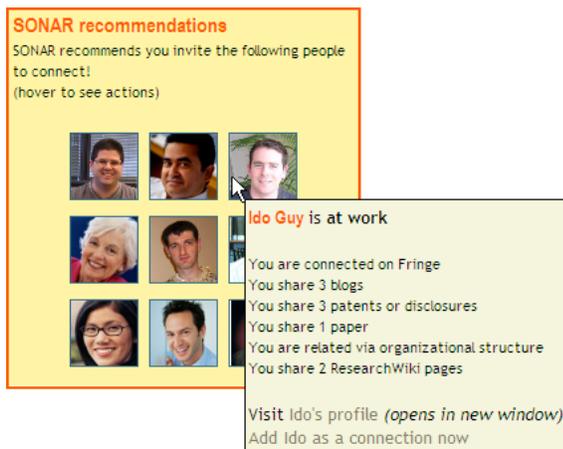


Figure 3 Recommender widget on home page

We compute the personalized recommendations by retrieving from SONAR the top 100 related/familiar people for each new user. We then filter this list to only include Beehive members as we wish to make recommendations of people who are already members of the community. We employ two different methods for ranking this list and determining which are the nine people to recommend: in one method, candidates are ordered by their SONAR familiarity score, in the other they are ordered by their activity level within Beehive, where activity is determined by a points system [7]. The rationale for the second method is that if users connect to more active people (from a pool of 100 friends), they will have more opportunities to learn from friends [2]. Clicking on the name or image of a recommended person allows users to visit the profile page of the proposed individual. In addition to the recommendations during the sign-up process, our system makes further people recommendations to users through a recommendation widget on their home page (Figure 3), within the first 48 hours of membership. The widget shows only the recommendation candidates photos; the user must hover to see further information and make a connection. Connecting to a recommended person using the widget refreshes the widget to include the next recommendation in line.

The second type of sign-up recommendation aims to encourage users to add some information about themselves to their profile page. The About You section in one's profile Figure 4(A) provides a platform on which conversations often occur and responses to this content would increase the sense of reciprocation. Thus we present the users with a set of 8

personalized About You recommendations with text boxes into which users supply their answers as appropriate. We also encourage users to add an About You of their own creation. Figure 4(B) shows a screen shot of the About You recommendation interface.

The About You recommendation candidates are drawn from a pool of over 4,500 unique entries and are selected due to their existence in the new user's network – the Beehive network if one was created earlier in the sign-up process, or the SONAR network otherwise. It is sometimes the case where a user's network will not contain sufficient About You entries. When this occurs, the list of recommendations is completed by randomly selecting from the top 30 most popular About You entries on the site.



Figure 4 (A) Sample About You entries. (B) Example recommended About You questions

4. EVALUATION

In order to assess the impact of making people and About You recommendations on the adoption of Beehive, we studied new users of the system using different configurations of the recommendation strategies described in the previous section. The study examines 1,118 users who joined the site over a 2 months period in autumn of 2008, and follows their activities on the site for a period of 4 months. The study includes worldwide IBM employees from all divisions of the company including managers, engineers, researchers, consultants, sales people, etc.

4.1 Methodology

As users signed-up for Beehive, they were randomly assigned to one of five groups: one control group receiving no recommendations (*ctrl*), two people only recommender groups (*ppl-familiar*, *ppl-active*), one About You only recommender group (*about-you*), and one combined recommender, which presented both people and About You recommendations (*ppl-familiar+about-you*). This setup allowed us to investigate the impact of different ordering and recommender strategies. The groups were assigned randomly and contained between 215 and 242 users with an average group size of 225 (Table 1). The two people-only recommendation groups differed in the ordering of the top 100 friends from which recommendations are selected, as described in Section 3. The *about-you* group received only recommendations of content (About You entries) to create. This

group did not have an explicit social network at this stage of sign-up, and the recommendations were based on their SONAR network. Another alternative was to present these users with the most popular About You entries; however previous research indicates that network based recommendations are received better [9] and continuously recommending the most popular items only serves to make them more popular. The final group *ppl-familiar+about-you* received people recommendations ordered by familiarity and about-you recommendations based on the network created through the people recommendation process. We excluded 18% of all new users because SONAR was not able to find matching Beehive users to recommend, i.e., the people found by SONAR were not Beehive members yet.

Table 1. Experimental groups.

Group	#users	People	Content	Ordering
ctrl	242	-	-	-
ppl-familiar	232	y	-	familiarity
ppl-active	215	y	-	Activity
about-you	217	-	Y	familiarity
ppl-familiar + about-you	217	y	Y	familiarity

We monitored each of the 1,118 users in our dataset for their first week of membership to see the initial impact of the recommenders and their first 4 months in order to assess the longer-term effects of the algorithms.

4.2 Results

We hypothesized that by introducing recommendations into the sign-up process we would achieve better populated profiles and better friendship networks leading to more engaged users. In the following sections we split the analysis into the direct effects of the recommenders and the overall impact on the behavior of the experimental users on the site.

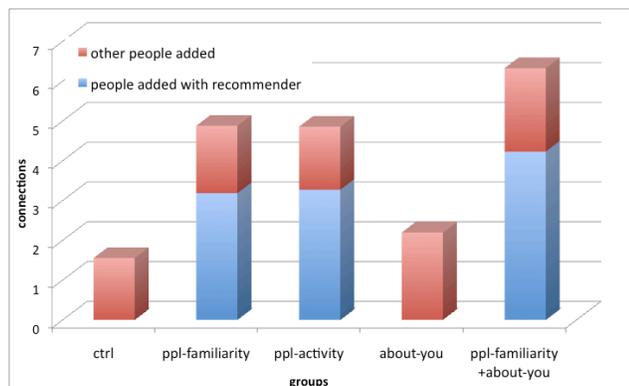


Figure 5 Connections made by each group

Direct Effects

We first examine the average number of connections created by members of each group, as depicted in Figure 5. The data shows that the groups that received people recommendations created significantly more connections ($F(4,1118)=29.79$, $p<0.01$), showing that people who received recommendations created larger articulated networks. Overall the acceptance rate of people recommendations was 45.3%, with 67% of the users who received recommendations accepting at least one.

Among the groups who received people recommendations, the *ppl-familiar* and *ppl-active* groups behaved similarly with the acceptance rates of recommendations varying by less than 1%. This suggests that ranking recommendations according to activity might not affect the users' likelihood to friend. We compare these two groups again in the next section. A Tukey post hoc shows a significant difference in the number of connections made by members of the *familiarity+about-you* group ($M=6.32$) when compared to the *ctrl* ($M=1.55$), *ppl-familiar* ($M=4.87$), *ppl-activity* ($M=4.85$) and *about-you* ($M=2.19$) groups ($p<0.05$). Members of the *ppl-familiar+about-you* group seemed to request more recommendations (by accepting recommendations and receiving the next recommendations in line) from the system. This shows that the About You recommendations are effective in terms of network enrichment if they come in addition to explicit people recommendations.

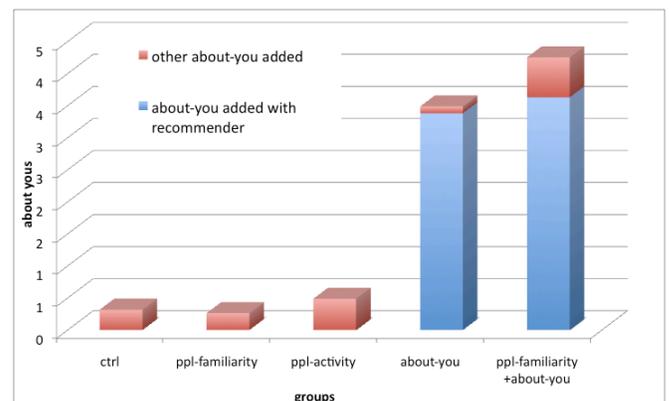


Figure 6 You entries added by each group

We examined the total number of About You entries added to profiles across the experimental groups (See Figure 6). The number of About You entries per user in the control group was 0.32 compared to 3.49 in the *about-you* group and 5.25 in the *ppl-familiar+about-you* group ($F[4,1118]=105.3$, $p<0.05$). As expected, the presence of the recommender significantly increased the amount of information that users contributed to their profiles. Tukey post hoc analysis shows that after the sign-up process and without the prompting, the *ppl-familiar+about-you* group ($M=4.25$) added significantly more About You entries (0.76) when compared to the *about-you* group ($M=3.48$), $p=0.05$. Users in the *ppl-familiar+about-you* group do not differ significantly from the *about-you* group when considering the acceptance rates of About You entries (45% versus 48% respectively), indicating that the selection of the candidates from the SONAR generated network (*about-you*) versus a user articulated network (*ppl-familiar+about-you*) did not have a substantial effect.

Overall Effects

Beyond the direct effects of the recommendations on the connections and the number of About You profile entries, we analyzed contributions, viewing, and return rates of each group. To gain an understanding of the longer-term effects of our recommenders, we inspected the users' cumulative activity levels after 4 months of membership.

In order to ascertain whether encouraging users to populate their profiles with connections and content also encouraged them to contribute other types of content such as photographs, shared lists, events, and status messages, we examined the overall content contribution of users (actions) in Beehive. In both the initial 7-day and the 4-month analyses significant differences between the groups were uncovered ($F[4,1118]=4.89$, $p<0.05$ over 7 days and $F[4,1118]=3.87$, $p<0.05$ over 4 months). Figure 7 shows the average contributions per group over 4 months. In both data sets the most noticeable finding is the high activity of users in the *ppl-familiar+about-you* group. Tukey post hoc analysis after 7 days reveals that the *ppl-familiar+about-you* ($M=2.02$) users contributed significantly more content than the *ctrl* ($M=1.15$), *about-you* ($M=0.7$), and *ppl-familiar* groups ($M=1.1$), where $p<0.05$. After 4 months the significant difference remains between the *ppl-familiar+about-you* and all other groups except the *ppl-active* group where $p<0.05$. This data suggests that combined people and About You recommendations are effective in creating sustained, long-term user engagement with the site.

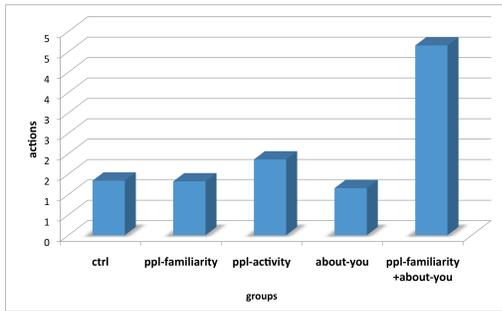


Figure 7 Actions over 4 months

Another metric for engagement examines the exploratory interactions (page views) of each group. Once again the clear outlier in both the 7-day and 4 month analysis was the group who received both forms of recommendation (*ppl-familiar+about-you*). The results of the 7-day analysis show significant differences between the groups (*ctrl* $M = 20.93$, *about-you* $M=18.76$, *ppl-familiar* $M=17.85$, *ppl-active* $M=23.60$, *ppl-familiar+about-you* $M=33.82$, $F[4,1118]=6.3$, $p<0.01$). Tukey analysis showed that the *ppl-familiar+about-you* group viewed significantly more pages than all other groups when $p<0.05$. The results of the longer analysis (see Figure 8) showed that the *ppl-familiar+about-you* group had significantly higher viewing than all other groups other than the *ppl-active* group. Finally, one may notice that the *about-you* group performs even worse than the *ctrl* group when it comes to actions and viewing, however these differences were not significant (we refer to them again later in this section).

We see from this longer term data that there are differences in the performance of the two people-only recommendation groups with the *people-active* group outperforming the *ppl-familiar* groups in both contributing and consumption of content, suggesting that recommending more active people can create long term, sustained engagement of new users.

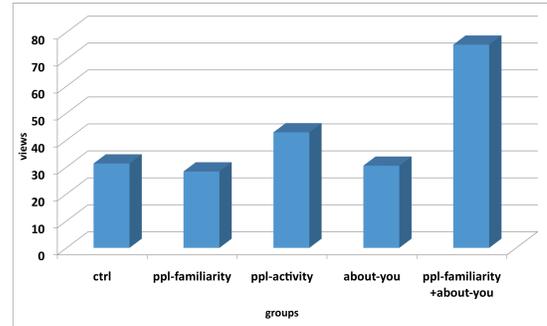


Figure 8 Views over 4 months

Cumulative interaction counts over a 4-month period only tell part of the story. We also examined the effect of each recommendation strategy on the return rate of the users in each group (see Figure 9). We monitored users' visits over a period of 4 months. For each group, and for each week, we calculated the percentage of users who were considered still active, i.e., contributed or viewed that week or in the weeks following inactivity is a hard feature to judge in systems where users can return as often as they see fit. Users may not visit a site for a period of days, weeks, and sometimes even months. Since our data is based on 4 months of monitoring, its main value is in showing the relative differences between the groups rather than to report an accurate return rate of a SNS. We opted here to show return rates for the first 3 months only as the data for the last month is likely to be skewed as we assume that users who fail to return over the last month of monitoring have dropped out of the system. In other words, we avoid the situation where users with less than one month of inactivity (weeks 13-16) are considered as inactive.

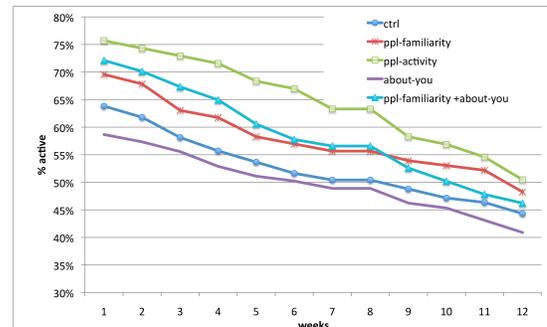


Figure 9 Return rates of each group over 12 weeks

Here we see a change in the trends seen in other analysis. When considering the long-term stickiness of the system the group who are introduced to active users (*ppl-active*) retain a larger percentage of its members over the 4 month period. We see a clear difference in the retention rates at the end of week 1 with the *about-you* and *ctrl* groups losing between 35% and 42% of users in comparison with the *ppl-active* group losing only 24%

This shows that users who received people recommendations are more likely to continue returning to the site, with people who received recommendations to active people being even more likely to return than others. Retaining almost as many users as the *ppl-active* are the *ppl-familiar* and *ppl-familiar+about you* with the group receiving both recommendation types outperforming its close counterpart for the most part.

A surprising outcome is that across most of the 4 months, users in the *about-you* group are less likely to return than those who receive no recommendations. We suggest that the effort exerted by users in creating About You entries did not result in immediate benefit to these users, leaving them feeling dejected. In contrast, in the case of friend recommendations the new users will receive positive responses in the form of friend request acceptances early in membership enhancing the sense of impact and community belonging. In any case, the return rate analysis reinforces the finding that content creation recommendations are most effective when combined with people recommendations.

4.4 Discussion

The results above show that early recommendations are effective in influencing new members to make more connections and create more profile entries, with all users who received recommendations outperforming the control group. Our data shows that the group who received both recommendation types outperforms the single type recommendations in terms of connections and About You contributions. The direct results of the recommender intervention are members with a larger articulated network and a richer profile. In terms of the vivacity of the system, we have encouraged users to contribute more content and initiate friendships. Beyond this, we have created a much more informative representation of each user early in their memberships, which could be harnessed to create more detailed user profiling of newcomers for further recommendation strategies, targeted advertising, etc. This is not to say that only the combination of people and content creation will have this effect. More analysis is necessary to determine if other combinations would produce similar or even better results.

The improved performance in the group who received both recommendation types (people and content for creation) is reinforced when we examine the indirect results of the intervention in the form of user participation in the long term.

Across two participation measures (contributing and viewing), only the group who received both recommendation types significantly outperformed the control group and in fact all other groups except the *ppl-active* group over a 4 month period. This finding shows that simply making recommendations of either content for creation or people does not have a significant effect on increasing user representation on a social network site.

The long term retention analysis showed that even though users in the *ppl-familiar+about-you* group may have larger articulated

networks, more detailed profile pages and may view content in greater numbers than the other groups, it is the users who receive recommendations to friend active people on the system who are most likely to continuously return to the system in the long term. This corroborates with the findings of Burke et al. [2], that learning from friends (especially if they are highly active) has a positive effect on engagement, and receiving feedback has a positive effect on return rate.

This suggests that there is superiority to selecting and ordering users based on overall activity on a social networking site. Previous work on people recommenders [13] applied ordering by strength of relationship, but based on our findings, sorting top friends by activity level may be a more suitable alternative.

5. CONCLUSIONS AND FUTURE WORK

Despite the phenomenal success and popularity of social media sites and in particular social network sites, some users will fail to engage with these systems and become inactive early in their membership. Drenner et al. [6] have shown that asking users to apply ratings and tags to existing content during sign-up can increase the performance of personalized recommender systems and user activity on the site. Our work contributes to the understanding of this kind of early intervention and to previous work on adoption [8], [14], [23] through the direct application of recommender technologies during the bootstrapping process of new users to social media sites. The cornerstone of our approach is the usage of aggregated social relationship information gathered across different types of external sources. This kind of information enabled us not only to recommend key people to connect to, but also to leverage those people to make subsequent recommendations for content creation. This enhances previous findings on recommendations for content creation that exploited existing social relationships on a [10].

The results of a live user trial with over 1,000 participants revealed various levels of direct and indirect impact across varying recommender strategies, when tested with newcomers to the system. In terms of connections and profiles, all users who received recommendations showed improvement over the control group for the content type(s) recommended. However, with respect to engagement, only users who received both people and content recommendations showed significant increases in terms of viewing, and contribution. This shows that the combination of recommending people to connect to and profile entries to create is the most effective method in encouraging users to consume and contribute more with the site, making it more lively. In terms of long-term retention, while this group retained a reasonable amount of users, it failed to outperform the retention rates of the group who were introduced to active users. This is logical when one considers that users who are highly active in terms of contribution as in this case are generating new content for their friends consumption and learning, frequently providing motivation for their friends to return more often. The findings of this part of the study motivate the first portion of future work, coupling the recommendation of active people with the recommendation of about me's which given the results found here we expect to be a promising combination. We would expect that the retention rates of a group of this format could outperform the contribution, viewing and retention of users in the top performing groups of this study.

Further future work includes exploring other recommendation types, in particular recommendation of content for consumption,

e.g. relevant events, photos, or shared lists. We believe that combining appropriate algorithms for content consumption with the existing people and content creation recommendations may enhance the engagement effects the recommender system achieves even further. We also intend to study our “newcomer recommender” for different social media sites, such as Blogs, Wikis, etc. Further to this, we plan to implement an equivalent recommender system outside the firewall. While this work's recommendations are based on SONAR, a system that is currently implemented within IBM, analogous recommenders can be investigated for sites outside the firewall.

6. ACKNOWLEDGMENTS

This work has been partially supported by Science Foundation Ireland through Grant No. 07/CE/I1147. We are indebted to Sigalit Ur and the Beehive team, Beth Brownholtz, Casey Dugan and Joan DiMicco for giving us access to their users.

7. REFERENCES

- [1] Bonhard, P. and Sasse, M. A. 'Knowing me, knowing you' - Using Profiles and Social Networking to Improve Recommender Systems. *BT Technology Journal* 24, 3(2006), 84-98.
- [2] Burke, M., Marlow, C., and Lento, T. Feed Me: Motivating Newcomer Contribution in Social Network Sites. *Proc. CHI'09*, (2009).
- [3] Chen, J., Geyer W., Dugan C., Muller, M., Guy I. Make New Friends, but Keep the Old – Recommending People on Social Networking Sites. *Proc. CHI'09*, (2009).
- [4] comScore, Inc. Retrieved from <http://www.comscore.com/press/release.asp?press=2698> on 29/01/09.
- [5] DiMicco, J.M., Millen, D.R., Geyer, W., Dugan, C., Brownholtz, B. and Muller, M. Motivations for Social Networking at Work. *Proc. CSCW'08* (2008), 711-720.
- [6] Drenner S., Sen S., and Tarveen L. Crafting the Initial User Experience to Achieve Community Goals. *Proc. RecSys'08*, (2008), 187-194.
- [7] Dugan, C., Geyer, W., Muller, M., DiMicco, J.M., Brownholtz, B. and Millen, D.R. It's All 'About You' - Diversity in Online Profiles. *Proc. CSCW'08*, (2008), 703-706.
- [8] Farzan, R., DiMicco, J., Millen, D. R., Dugan, C., Geyer, W. and Brownholtz, E. Results from deploying a participation incentive mechanism within the enterprise. *Proc. CHI'08*, (2008), 563-572.
- [9] Facebook Statistics, 2008. Retrieved from <http://www.facebook.com/press/info.php?statistics> on 29/01/09.
- [10] Geyer, W., Dugan, C., Millen, D.R., Muller, M., Freyne, J. Recommending Topics for Self-Descriptions in Online User Profiles. *Proc. RecSys'08*, (2008), 59-66.
- [11] Groh, G., and Ehmig, C. Recommendations in Taste Related Domains: Collaborative Filtering vs. Social Filtering. *Proc. Group'07*, (2007), 127-136.
- [12] Guy, I., Jacovi, M., Shahar, E., Meshulam, N., Soroka, V. and Farrell, S. Harvesting with SONAR: the value of aggregating social network information. *Proc. CHI'08* (2008), 1017-1026.
- [13] Guy I., Ronen I., Wilcox E. Do You Know? Recommending People to Invite into Your Social Network. *Proc. IUI'09*, (2009).
- [14] Harper, F.M., Frankowski, D., Drenner, S., Ren, Y., Kiesler, S. Terveen, L., Kraut, R., and Riedl, J. Talk Amongst Yourselves: Inviting Users to Participate in Online Conversations. *Proc. IUI'07*, (2007), 62–71.
- [15] Herlocker, J. L., Konstan, J. A., Borchers, A., and Riedl, J. An algorithmic framework for performing collaborative filtering. *Proc. SIGIR'99*, (1999), 230-237.
- [16] Kohrs, A., and Merialdo, B. Improving Collaborative Filtering for New Users by Smart Object Selection. *Proc. ICMF 2001*
- [17] Markus, M. L. Toward a Critical Mass Theory of Interactive Media: Universal Access, Interdependence, and Diffusion, *Communications Research*, 14(5), 1987, 491-511
- [18] Rashid, A. M., Albert, I., Cosley, D., Lam, S. K., McNee, S. M., Konstan, J. A., and Riedl, J. Getting to Know You: Learning New User Preferences in Recommender Systems. *Proc. IUI'02*, (2002), 127-134
- [19] Sinha, R. and Swearingen, K. Comparing Recommendations made by Online Systems and Friends. *Proc. DELOS-NSF Workshop on Personalization and Recommender Systems in Digital Libraries*, (2001).
- [20] Smith, M.A. and Kollock, P., "Communities in Cyberspace" (199) In *Communities in Cyberspace*, Routledge, London, 1999.
- [21] Spertus, E., Sahami, M., and Buyukkokten, O. Evaluating similarity measures: a large-scale study in the Orkut social network. *Proc. SIGKDD'05*. (2005), 678-684.
- [22] Stecher, K., Counts, S. Thin Slices of Online Profile Attributes. *Proc. ICWSM'08* (2008).
- [23] Sun, L. and Vassileva, J. Social Visualization Encouraging Participation in Online Communities. *Groupware: Design, Implementation, and Use*, 349—363, 2006