Social Networking Feeds: Recommending Items of Interest

Jill Freyne, Shlomo Berkovsky
Tasmanian ICT Center, CSIRO
GPO Box 1538, Hobart, 7001,
Tasmania, Australia
firstname.lastname@csiro.au

Elizabeth M. Daly, Werner Geyer
IBM T.J Watson Research,
One Rogers Street, Cambridge,
MA 02116, USA
firstname.lastname@us.ibm.com

ABSTRACT

The success of social media has resulted in an information overload problem, where users are faced with hundreds of new contributions, edits and communications at every visit. A prime example of this in social networks is the news or activity feeds, where the actions (friending, commenting, photo sharing, etc) of friends on the network are presented to users in order to inform them of the network activity. In this work we endeavour to reduce the burden on individuals of identifying interesting updates in social network news feeds by automatically identifying and recommending relevant items to individuals where item relevance is based on the observed interactions of the individual with the social network. The results of our offline study show that combining short term interest models, exploiting previous viewing behavior of users, and long-term models, exploiting previous viewing of network actions, was the best predictor of feed item relevance.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces; H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval

General Terms

Experimentation, Algorithms

Keywords

Personalization, Social Network, Relevance, Feeds

1. INTRODUCTION

Information overload is a well documented problem in the context of the Web. In recent years, it has been compounded by the popularity of sites and systems, which promote the creation of user generated content. These include content sharing sites, such as YouTube and Flickr, blog hosting sites, such as Blogger and BlogNow, and social networking sites, such as Facebook and MySpace.

The popularity of social networks has surpassed all expectations [2] with Facebook alone reporting 400 million active users, with average user having 130 friends and spending 55 minutes a day on the site [1]. These users contribute content such as photos and videos, join groups, make friends, post comments, and explore the content contributed by others. Social networks use news or activity feeds as a way of keeping users up to date with the actions of their friends. But, with the frequency of visits, high number of actions and friends, it can be difficult for people to identify the feed items, in which they have a genuine interest.

In this work investigate how to improve social network news feeds by making recommendations for individual items through the use of personalization techniques. We propose determining the relevance of users and actions to individuals as a basis to recommend relevant network activities. The relevance could be exploited to generate a personalized recommended subset of feed items reducing the problem of information overload. We investigate which interaction types are most predictive of user interest and how short and long term user interest models can be exploited for this purpose. We develop several techniques, scoring the relevance of news feed items according to user actions, such as friending, browsing, and interacting with other users, and evaluate these techniques using the interaction logs of IBM's SocialBlue (previously known as Beehive) social network users.

2. SOCIAL NETWORK ACTIVITY FEEDS

Social networks strive to keep users up to date with their friends activities on the network by including *news* or *activity* feeds in their home pages. The content of the feed relates to the actions of a target user's friends and generally informs the user of new content contributed (photos, groups, comments), new friendships made, groups joined, status message updates and other actions. Each item in the news feed comprises four components: the *subject*, who carried out the action, the *action*, which caused some change in content or state of the network, the *object*, on which the action was carried out (could be a user for friending actions or a content for posting or browsing actions), and the *time*, at which the action occurred.

The area of feed generation has been gathering much attention with Facebook recently being granted a patent [7] in dynamic news feed generation. Initial recognition of the information overload problem in network feeds has also been seen. Some social networks, e.g. Facebook and MySpace,

RecSys2010, September 26–30, 2010, Barcelona, Spain.

allow users to filter users or actions from their feeds, but this requires users to spend time customising their feeds and block users or actions from appearing in the feed unless re-activated. Facebook also offers multiple views of feeds based on popularity and recency. The standard method of network feeds' delivery is a reverse chronologically ordered list, which shows all the activities of a user's friends. However, it is unrealistic to assume that each and every action of each and every friend is of a genuine interest to a user. Additionally, the activities of a highly active user may flood the ordered list, causing more relevant events to be missed. Our work aims to uncover approaches for recommending feed items to users. We determine feed relevance in a personalized manner by estimating user interest in both other users and actions. We hypothesise that this will allow us to recommend users and actions of highest interest and generate more informative and relevant news feeds to the user.

3. JUDGING FEED ITEM RELEVANCE

Traditional feeds judge relevance according to the activity time, which obviously eliminates any degree of personalization. We determine the relevance of a network activity item in the feed to a user by examining the observed user interactions of the individual over a period of time. To do this, we propose scoring the feed item based on all the components: *user*, *action*, *object(s)* and *date*. In this work we focus on only the *user* and the *action* involved in a feed item and propose a way of quantifying the predicted interest level and, thus, the relevance of a feed item to a user.

3.1 Action Relevance

We propose judging the relevance of an action, a_c, to a target user, u_T in two ways. Firstly, we measure the regularity with which u_T performs a_c, e.g., *posts* a photo or *creates* a group between days d_m and d_n. Secondly, we measure the regularity with which u_T views content created as a result of another user performing a_c, e.g.,*views* photos or *views* group pages between days d_m and d_n. As actions inherently have various applicability frequencies, i.e., some are done more frequently than others, we measure regularity as the ratio between the number of days where an action occurred and the number of days where it could have occurred, i.e., the user logged in[1]. Equations 1 and 2 present the action centric relevance judgements.

$$Action_{int}(u_T, a_c, d_m, d_n) = \frac{\sum_{i=m,..,n} Interact(u_T, a_c, d_i)}{\sum_{i=1,..,n} Login(u_T, d_i)} \quad (1)$$

$$Action_{view}(u_T, a_c, d_m, d_n) = \frac{\sum_{i=m,..,n} View(u_T, a_c, d_i)}{\sum_{i=1,..,n} Login(u_T, d_i)} \quad (2)$$

$Interact(u_T, a_c, d_i)$ and $View(u_T, a_c, d_i)$ denote the indicators of interaction between user u_T and action a_c on day d_i or viewing of content created by another user by completing action a_c on d_i. $Interact(u_T, a_c, d_i) = 1$ if u_T

[1]Counting the occurrence days is a course measure and only partially normalizes the different applicability frequencies. More fine grained methods, including decay models and average user frequencies, will be investigated in the future.

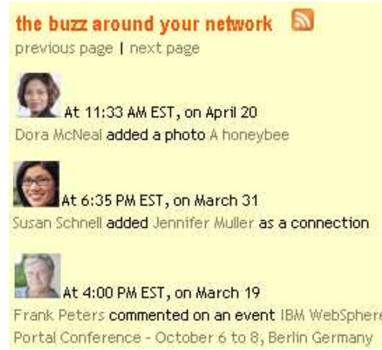

Figure 1: Feed example from SocialBlue

interacted with a_c on d_i and 0 otherwise and, similarly, $View(u_T, a_c, d_i) = 1$ if u_T viewed content created as a result of performing a_c on d_i and 0 otherwise.

3.2 User Relevance

We propose judging the relevance of a user, u_b, to a target user, u_T, in two ways. Firstly, we measure the regularity with which u_T directly interacts with u_b, e.g., *post* a message on the message board of u_b or *comments* on the content published by u_b. Secondly, we measure the regularity with which u_T views content created by u_b, e.g.,*views* the profile page of u_b or *views* photos published by u_b. Once again these measures are between days d_m and d_n. Other metrics such as mutual friends, common groups and the content of exchanged messages have been investigated as measures of tie-strength in social networking by [4, 6] but here we stick to this simple measure.

Similarly, we resolve the frequency variability by using day based indicators of interaction or content viewing. Equations 3 and 4 present the user centric relevance judgements.

$$User_{int}(u_T, u_b, d_m, d_n) = \frac{\sum_{i=m,..,n} Interact(u_T, u_b, d_i)}{\sum_{i=1,..,n} Login(u_T, d_i)} \quad (3)$$

$$User_{view}(u_T, u_b, d_m, d_n) = \frac{\sum_{i=m,..,n} View(u_T, u_b, d_i)}{\sum_{i=1,..,n} Login(u_T, d_i)} \quad (4)$$

$Interact(u_T, u_b, d_i)$ and $View(u_T, u_b, d_i)$ denote indicators. $Interact(u_T, u_b, d_i) = 1$ if u_T interacted with u_b on d_i and 0 otherwise and $View(u_T, u_b, d_i) = 1$ if u_T viewed content created by u_b on d_i and 0 otherwise.

3.3 Long and Short Term Relevance

Both the user and action based relevance judgements can be determined over a short or long term basis. Long term interest models represent the stable interests of users, gathered over the lifetime of their membership in the social network. In contrast, short term interest models are likely to be represent their current relevance judgements centered around the days or weeks prior to a feed generation. Hence, the time frame of Equations 1, 2, 3, and 4 may vary in order to reflect the preferred granularity of the relevance judgements.

4. EVALUATION

We conducted an offline evaluation using the interaction logs of SocialBlue [3]. SocialBlue's news feed, known on the site as the Buzz, is displayed immediately after a user's login and accessible throughout a session. The feeds include 17 types of actions, such as the addition of friends, photos, events, profile entries, comments on content, recommendations, and updates of status messages. 15 items are displayed on a single page, with additional items available on request. Figure 1 shows a sample feed with 3 items.

The purpose of the analysis is to determine the suitability of two relevance models, a short term model that captures the interactions over a 1 month period and a long term model that covers the entire membership, in generating relevance scores. Further to this, we compare the performance of the 4 relevance judgement algorithms presented in Section 3: two *action* based and two *user* based.

4.1 Set Up and Methodology

We selected 1800 of the most recent instances of browsing initiated through the activity feeds. To investigate long and short term relevance models, we selected instances related to users who had been a member of SocialBlue for 6 months or more. For each click, we determined the actual news feed shown to the user, i.e., the 15 most recent actions carried out by the user's friends. We also generated two alternative feeds sets for each algorithm denoted by Equations 1-4. The first exploits a *long term* relevance model, i.e., d_1 is the first day of membership. The second exploits a *short term* relevance and focuses on interactions in one month prior to the feed generation, i.e., $d_1 = d_n - 31$. In both cases, d_n is set to the day the feed was generated.

Equations 1-4 were used to rank the items in the alternative feeds by allowing the relevance of a feed item f_i to be determined by the relevance of the user or action components as determined by the equations.. For example, the $Action_{int}$ algorithm was used to assign relevance scores to each feed item and the items in a list denoted as $Action_{int}$ were ordered by decreasing relevance scores. Similarly, Equations 2-4 were used to generate the $Action_{views}$, $User_{int}$ and $User_{views}$ lists, respectively. We compare the performance of the relevance judgement approaches by examining the ranked position of the selected items in the lists, favoring lists that placed the selected items at the top.

4.2 Results

When considering the performance of each relevance metric in this offline study, we compare the performance of the personalized algorithms against each other, rather than with the time based algorithm used in SocialBlue. Research into trust and display positions of ranked lists have shown that users' selection is strongly influenced by the ranking of list items [5] and we hypothesise that ranking factors would have influenced the users of SocialBlue. We noted strong preferences for feed items presented at the top of the result lists shown to SocialBlue users, with 50% of selections being made on feeds in the top two positions in the feed lists and 75% of selections within the first 5 result positions. Thus, the performance of personalized approaches in comparison to the time based metrics are best evaluated in an online live user study and here we concentrate on comparing the personalized approaches. We note however that the average position of a clicked feed item in the feeds presented to the users in Social Blue was 3.47.

Table 1 shows the average position of the selected feed items in each personalized feed, for both time frames con-

	Action		User		View
	interact	view	interact	view	
long	7.356	7.037	7.634	7.294	6.606
short	8.376	7.498	7.783	6.522	6.263
combined					6.151

Table 1: Average rank of clicked feed items.

sidered. Note that lower positions indicate higher ranks in the feed and better performance. When judging the relevance of the *action* components of a feed item, the *long term* relevance model outperforms the *short term* model. The long term model places the feed items at position 7.356 and the short term model at 8.376 for the $Action_{int}$ and, respectively, at positions 7.037 and 7.498 for the $Action_{view}$. T-tests revealed significant differences in performance between the models at $p < 0.05$. We see also that regardless of the interest model used the $Action_{view}$ approach outperforms the $Action_{int}$ approach, again significant at $p < 0.05$.

In contrast, when judging the relevance of the *user* components of a feed item, the *short term* relevance model outperforms the *long term* model. For the $User_{int}$ approach, positions of the *long term* and *short term* models are, respectively, 7.634 and 7.783, but the difference between the two is not statistically significant. For the $User_{views}$ approach, the positions are, respectively, 7.294 and 6.552, and the difference between the short term and the long term model is statistically significant at $p < 0.05$. Again, regardless of the interest model, the best performing approach is the one which examines the viewing behavior of the users.

These relevance judgements consider a single component of the feed item, either the user or the action. As in both cases viewing behavior outperformed the action/interaction behavior, we generated another list for which we consider the relevance of both actions and users. We compute the combined relevance score $View(u_T, f_i, d_m, d_n)$ for feed item f_i by averaging the action viewing relevance $Action_{view}(u_T, a_i, d_m, d_n)$ and the user viewing relevance $User_{view}(u_T, u_i, d_m, d_n)$ scores where u_i is the user component of f_i where a_i is the action component of f_i. The results of this combination, 6.606 for the long term and 6.263 for the short term model, outperform the best performing individual approaches in both models (statistically significant at $p < 0.05$), illustrating the contribution of both components of the feed items relevance. Further to this, we note that the performance of the short term model's $View$ algorithm significantly outperforms that of the long term interest model at $p < 0.05$.

$$View(u_T, f_i, d_m, d_n) = \frac{Action_{view}(u_T, a_i, d_m, d_n) + User_{view}(u_T, u_i, d_m, d_n)}{2} \quad (5)$$

Our comparison of the long and short term models across users and actions however suggests that for optimal performance we should *combine* the relevance of actions from the long term relevance model and of users from the short term model. Thus, we compute the combined relevance score $CombinedModels$ by averaging the long term action viewing relevance $Action_{view}(u_T, a_c, d_m, d_n)$ where d_n is the day the feed is generated d_m is u_t's join date and the short term user viewing relevance $User_{view}(u_T, a_c, d_m, d_n)$ in which $d_m = d_n - 31$ scores as in Equation 6.

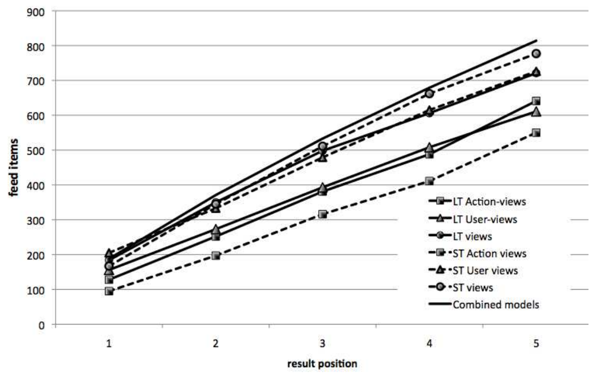

Figure 2: Position of clicked feed items

$$CombinedModels(u_T, f_i, d_m, d_n) = \frac{Action_{view}(u_T, a_i, d_m, d_n) + User_{view}(u_T, u_i, d_{n-31}, d_n)}{2} \quad (6)$$

The result of this combination is an average position of 6.151 which significantly outperforms that of the long term *views* model (p<0.05) but does not significantly outperform that of the short term $Views$ algorithm which suggests that the user views interest model is of core importance to the performance of the $Views$ approaches.

The average rank of clicked items in Table 1 shows only the overall performance of each approach. Thus, we examined the performance of each algorithm by examining the spread of feed items across the feed lists. Figure 2 shows the performance of the approaches in terms of the number of clicked feed items placed at each news feed position or higher[2]. For example, at result position 2, the markers represent the number of clicked items, placed at position 1 or 2. The short term relevance models are represented by dashed lines and the counterpart, long term models, by a solid line. The larger the number of clicked feed items placed high in the feed, the better the performance.

Examining the performance of the best performing action relevance approach, $Action_{views}$, the long term model places more feed items in positions 1-5 than the short term model. In contrast, for the best performing user relevance approach, $User_{view}$, the short term model outperforms the long term model. These differences are statistically significant across all 15 result positions at $p < 0.05$. Note the superior performance of the $View$ approach in each model and, more importantly, the out performance of all models by the *combined* approach, which exploits both the action and user relevance models.

5. CONCLUSIONS & FUTURE WORK

This work indicates the potential for personalized recommendation of social network events in a news feed. It points to the value of monitoring the interactions of users and also the viewing patterns of users to determine the relevance of users and actions on the network. Our offline study using the SocialBlue logs has demonstrated that short term relevance models are suitable for judging the relevance of network users, but that long term interest models are suitable for judging the relevance of carried out actions. Furthermore, our work shows that harnessing the browsing patterns of users, what and whom they view, are more accurate predictors of relevance than what actions they carry out or with whom they communicate.

While the performance of the developed relevance models and their combinations could be compared, their comparison to chronological feeds cannot be assessed in an offline evaluation. Hence, our next step is to incorporate our relevance models into a live social network, where our personalization could be applied not only to re-rank the feed items, but also highlight the most relevant activities that have been carried out since a users last login. This could result in a much more valuable service to social network users.

This work aims to determine the relevance of actions and users in a social network, but its impact could go far beyond the production of feeds. Determination of online strength of user relationships could be used for other recommendation purposes, including friend making, content sharing, and social recommendations. Similarly, determining user interest in action types could be used to determine user-user similarity or group interest models.

[2] Positions 6 to 15 and the $Action_{int}$ and $User_{int}$ approaches were omitted for graph clarity.

6. ACKNOWLEDGMENTS

This research is jointly funded by the Australian Government through the Intelligent Island Program and CSIRO Preventative Health Flagship. The Intelligent Island Program is administered by the Tasmanian Department of Economic Development, Tourism, and the Arts.

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