

Social Referral: Leveraging Network Connections to Deliver Recommendations

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ABSTRACT

Much work has been done to study the interplay between recommender systems and social networks. This creates a very powerful coupling in presenting highly relevant recommendations to the users. However, to our knowledge, little attention has been paid to leverage a user's social network to deliver these recommendations. We present a novel approach to aid delivery of recommendations using the recipient's friends or connections. Our contributions with this study are 1) A novel recommendation delivery paradigm called *Social Referral*, which utilizes a user's social network for the delivery of relevant content. 2) An implementation of the paradigm is described in a real industrial production setting of a large online professional network. 3) A study of the interaction between the trifecta of the recommender system, the trusted connections and the end consumer of the recommendation by comparing and contrasting the proposed approach's performance with the direct recommender system.

Our experiments indicate that Social Referral is a promising mechanism for recommendation delivery. The experiments show that a significant portion of users are receptive to passing along relevant recommendations to their social networks, and that recommendations delivered through users' social networks are much more likely to be accepted than those directly delivered to users.

Categories and Subject Descriptors

J.4 [Computer Applications]: Social and behavioral sciences

Keywords

Social referral, recommender systems, social network

1. INTRODUCTION

Social Recommender Systems incorporate social ties to either a) Augment relevance of the presented results [4] b) To

explain away the recommendation to the user by presenting social proof [3] or a combination thereof. These ideas are quite powerful in driving relevant engagement from the end user. However, not much attention has been paid in RecSys literature to leverage social ties to *deliver* recommendations. In this scenario a user's connection becomes the channel to route content to the incumbent. The aspects that come into play in this setting are 1) Connection strength or a measure of trust between the users on either side of the connection and 2) The reputation or topical social influence of the user.

Both of these aspects have been studied extensively [5]. We propose leveraging these ideas along with a traditional function of the recommender system i.e. recommending relevant content to the user to generate a *delivery* paradigm via the 'referral' mechanism. Consider how a content provider usually pushes recommendations to target users - They directly deliver relevant products/articles to users via email or online notification streams such as *Facebook Wall*. The interaction of the users' social network with this item is primarily used as a social proof to enhance the credibility of the recommendation. 'Social Referral' is the following alteration to this model : Upon a user's (actor) engagement with a piece of content (say movie, news article or music piece) we surface from their network, other users who will potentially be interested in this content. In this model the content provider does not directly engage with the target user, rather, they nudge the actor to refer this content to their social ties. The selection process of the referral recipients is guided by a function of 1) user-item relevance obtained from the traditional recommender systems and 2) user-user connection strength unveiled from the social network. In this fashion, network ties become effective channels to deliver peer endorsed recommendations i.e. *social referrals*. We describe the properties and efficacy of our system in the context of industrial recommender system for recommending professional groups to end users in a large online professional network. The architecture proposed here is generic and can be applied to any other social settings as well.

2. RELATED WORK

Much work has been done in incorporating Social signals in Recommender Systems. In [4] Kautz et. al. proposed a method to integrate social network with collaborative filtering. It has been shown in [1, 2] that incorporating social network information in traditional recommender improves the outcome of the system. Guy et al.[3] introduced the concept

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of aggregated familiarity relationships to recommend people to connect to within an enterprise SNS.

From a different perspective, Lerman [7] studied the effect of user recommended stories as opposed to stories recommended by a CF based system and identified that the users are more interested in the former. In a similar study [8], the authors compared movie and book recommendations from friends with online recommender systems and found that incorporating the source of the recommendation introduced a probable bias in favor of the former.

In social science the concept of adoption of ideas and technologies in the social network has been studied [6]. Algorithmic studies to identify influential people in the social network and how they instigate subsequent adoption has also been carried out in [5]. However, any data driven method to deliver recommendation via early adopters and aid them to choose potential followers has not fully been explored. In this paper, we present a system that leverages propagation of relevant group recommendation via group members and aids them to selectively identify a subset of their connections for group recommendation. The selection process takes into account the probable affinity of the potential member to the group and hence, the recipients are more likely to accept the recommendation.

3. PRELIMINARIES

We study Social Referral in the context of professional groups in a large online professional network. A recommendation system has been incorporated on this website that periodically calculates the relevance score of a group for a member. This score is subsequently used to recommend new groups for a member. Members can also share a group that he is a member of to his connections. However, group shares necessitate manual selection of connections which may lead to inclusion of members who may not have the same level of interest for the group or exclusion of potentially interested members. In order to bridge the gap between the group recommendation and group share, and aid members to select connections to share a group with, a seamless integration of these two sources of information is warranted.

Let $U = \{u_1, u_2, \dots, u_n\}$ be the set of users, $G = \{g_1, g_2, \dots, g_m\}$ be the set of groups. Let $\eta : u_i \rightarrow \hat{U} \subseteq U$ be a function that returns the neighbors of $u_i \in U$ and $\tau : u_i \times g_j \rightarrow \mathbb{R}$ be the relevance score of group g_j for user u_i . Then for a given k the objective here is for a 2-tuple (u_i, g_j) to identify $\hat{N} \subseteq U$ such that $\forall u_k \in \hat{N}, \tau(u_k, g_j) \geq \lambda \wedge u_k \in \eta(u_i) \wedge |\hat{N}| \leq k \wedge \forall s (s \in (\eta(u_i) \setminus \hat{N}) (\tau(u_k, g_j) > \tau(s, g_j))$, where λ is a predefined threshold. Thus for each member u_i , who we refer to as referrer from here on, and each group g_j , we generate a set of recommendation of top- k target users, \hat{N} from u_i 's neighbors, having a minimum relevance score of λ . Figures 1(a), 1(b) delineate the process. After the referrer joins a group, he is prompted to recommend the group to a subset of his network as shown in 1(a). This subset of potential target users are pre-calculated by the system and they are guaranteed to have a minimum level of affinity toward the group. Subsequently, each of the connections receive a personal group recommendation message from the referrer (Figure 1(b)).

4. METHOD

The current group recommendation framework on this website takes into account both content and social aspect

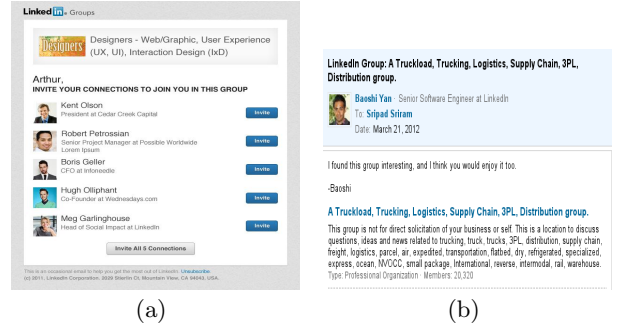


Figure 1: (a) Emails sent to referrers, (b) Emails sent to target users

for recommendation purposes. We piggyback off of this framework to obtain user-group affinity scores. This step guarantees that when a group subscriber refers a group to one of his connections, the connection is highly likely to be interested in the group. We also compute the connection strength between members. Since the calculation of connection strength is an orthogonal issue and can be done in a variety of ways, we use an existing in-house algorithm that, given a pair of members, returns the connections strength among them.

From an abstract level, for each (referrer, group) pair, the method searches the neighborhood of the referrer's social network and extracts group affinity scores for those neighbors for the group in question. The potential target users are then reordered based on group relevance score and their connection strength with the referrer.

4.1 Selecting target users

Each (referrer, group) pair can contain multiple target users that can be referred. However, the content of the group may not be equally relevant to all the target users. Analogously, the relationship between the referrer and the target user is also a salient attribute that contributes to the referral operation. We can recommend the target users with strongest connection strength in a members network to refer for a particular group. Alternatively, we could recommend the target users with highest recommendation score, or employ a hybrid approach. Since for each (u_i, g_j) pair we obtain a subset, \hat{N} of member u_i 's connections, we can obtain two different ordered list from \hat{N} i.e. $\pi_1 = (u_{i1}, u_{i2}, \dots, u_{i|\hat{N}|})$, where $m < n \rightarrow \sigma(u_i, u_{m1}) > \sigma(u_i, u_{n1})$ and $\pi_2 = (u_{i2}, u_{i22}, \dots, u_{i|\hat{N}|2})$, where $m < n \rightarrow \tau(u_{m2}, g_j) > \tau(u_{n2}, g_j)$. Here $\sigma(u_i, u_{m1})$ stands for the connection strength between u_i and u_{m1} . Subsequently, we can target top- k members from either of the two lists.

4.2 Identifying the most relevant group

For each referrer, there might exist multiple groups he/she could refer to his network connections. Instead of flooding the referrer with candidates for all these groups, we have chosen to select one group per referrer to recommend target users for based on different criteria. One criterion is group quality. We generate the quality of a group as a function of recent activity pertaining to that group. We generate the group quality score using the following equation: $Q(g_i) = \frac{\ln(1+c+p)}{\ln(\alpha+N)}$ Where c , p and N stands for the number of unique commenters, number of unique posters and the to-

tal number of members in the group and α represents a user defined parameter. This measure is generated for all the active groups considering their recent activity. The parameter α smoothes out the effect of group size with respect to their activity. Alternatively, for each group, we generate a set of potential recommendation target \tilde{N} for a specific member, we get: $R(u_i, g_j) = \frac{\sum_{u_k \in \tilde{N}} \sigma(u_k)}{|\tilde{N}|}$ where $\forall u_k \in \tilde{N}$, $\sigma(u_i, u_k)$ represents the connections strength between u_i and u_k . This measurement depicts the relevance of a group in terms of the average connection strength between the referrer and the target users. We have used both scores to select the group to recommend (named Better_GRP and Stronger_CONN respectively). Again, a combination of these two measures was also employed to compare performance: $RQ(u_i, g_j) = \ln(Q(g_j)) + \ln(R(u_i, g_j))$. Thus for each referrer, we choose the group with the highest score calculated by any of the three measures defined above and select from the referrer's connections, top- k potential recommendation targets.

5. EXPERIMENTS

Our goal is to test whether social referral is an effective channel for recommendation delivery. In designing experiments, there are two major questions we want to answer: 1) Are referrers receptive to passing along recommendations to their social network connections? 2) For target users, is there a significant difference in the acceptance rate of recommendations coming from social referral, and the acceptance rate of recommendations directly delivered to them? Furthermore, it is also worth investigating what factors affect a referrer's decision on whether to make a referral or not, and what factors affect a target user's decision on whether to accept a recommendation.

5.1 Methodology

The data we used for this experiment came from a professional network, and the kind of recommendation we used was group recommendation for the members of this professional network. We sampled a set of members who joined a group in the last 14 days. These were the referrers. On the other hand, we used an empirically proven in-house recommender system to compute top 100 group recommendations for each member. For each referrer we checked if the group the referrer just joined was also recommended to his/her network connections (aka friends) by the recommender system. Any of such connections is a target user to whom the referrer could make a referral of the group. An email was then sent to each of the referrer (Figure 1(a)). Each email contained links to five target users. A referrer could click on any or all of the five links, which will cause a group join invitation email to be sent to the clicked target user. A total of 85K emails were sent to referrers. As a control group for the experiment, we also sent out another set of recommendation emails directly to target user. The recommendation data and target user list were generated exactly in the same way as the first set of emails that were sent to referrers. The only difference here was that we bypassed the referrer and directly sent those recommendations to target users. A total of 16K emails were directly sent to target users.

5.2 Results

5.2.1 Referrer's Likelihood to Send Out Referral

How likely are referrers to send out a recommendation referral to their network connections? Our experiments showed that about 7.8% of referrers clicked on links in the emails to

send out a referral email to their network connections. This is a significant percentage which far outperforms average emails CTR's. Figure 3(a) depicts different referrer CTRs at connection strength (CS) where CTR denotes among all target users with connection strength less than CS , what fraction of them are referred. It showed that the higher the connection strength between the referrer and the target user, the higher the CTR is for the referrers. We also compared overall referrer CTR with referrer CTR's for algorithm Better_GRP, and algorithm Stronger_CONN (Figure 3(a)). The data indicates that for the same connection strength, referrers are more likely to click on a referral link if the quality of the recommended group is higher. This confirms our intuition that referrers are more likely to send referral to their closer friends, and more likely to recommend a group which they think is of a higher quality. Another interesting study we performed was to check if referrers's selections would lead to more relevant recommendations to the target users. It seems intuitive to think that a referrer might remove those recommendations they think are not relevant to the recipients. Figure 3(b) compares the distributions of recommendation relevance scores before and after referrer clicks. Surprisingly, it showed that the distributions of recommendation relevance scores are almost identical before and after referrer selection. The result indicates that for the recommendations produced by an effective recommender system, the referrers are unable to tell which recommendations are more relevant to their network connections.

5.2.2 Target User's Acceptance Rate of Recommendations

We compared the join rate for groups for group recommendations delivered via social referral and those directly delivered to target users (the control group in the experiment). Our experiments showed a strong join rate by target users for group recommendations coming from social referrals. In fact, group recommendations delivered via social referral have more than twice as large acceptance rate (22.5%) than those directly delivered to target users (9.6%) (Figure 2).

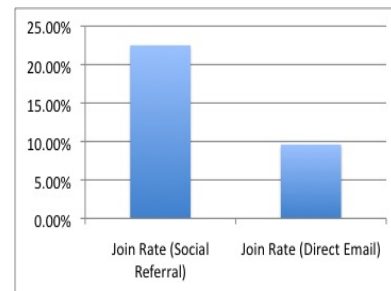


Figure 2: Join rate: Social referral vs. Direct delivery

In addition, as shown in Figure 4(a), there is evident correlation between the join rate and the connection strength CS between referrers and target users. The join rate here denotes among all target users with connection strength less than CS , what fraction of them have joined. The more strongly a target user is connected to a referrer, the more likely that the target user will accept a recommendation referral coming from the referrer.

The target user join rate is also affected by the relevance of recommendations and it is computed in a similar fashion as for Figure 4(a). Figure 4(b) showed that more relevant recommendations lead to higher join rates.

5.3 Discussion

One argument against the usage of the social referral is that direct recommendation seems more effective than the overall workflow of social referral. After all, in social referral there are two steps of loss for the recommendations: a recommendation could be ignored by the referrer, or the target user. Using the experiment setup in this paper, a piece of recommendation would have a 9.6% of chance to be accepted via direct recommendation email, but only 2.2% of chance via social referral. However, there are several attractive aspects about social referral. First, the user experience in social referral is better. Although the acceptance rate of 9.6% is significant for direct recommendations, it also means that over 90% of target users find the recommendations not useful. Adding to the fact that these were unsolicited recommendations coming from the system, a significant portion of users will likely be annoyed by them. In a social referral scenario, however, instead of receiving an unsolicited, cold recommendation, the target users receive warm recommendations coming from their network connections directly. Even though about 77% of target users still do not act on the recommendations, it is unlikely to annoy them as these are recommendations coming from their friends who act as filters on behalf of the system. Second, since referrers are already engaging with the recommended objects themselves, it is natural to piggyback the social referral process at various engaging points for free. Although we used emails for the pilot study in this experiment, emails are by no means the only, or the most efficient channel. For example, in the context of a professional social network, the referrals could be brought to a referrer's attention when the referrer joins a group, starts a group discussion, or follows a certain group discussion on the website. Finally, even with emails, an additional 2.2% acceptance rate is not to be easily dismissed for a lot of marketers.

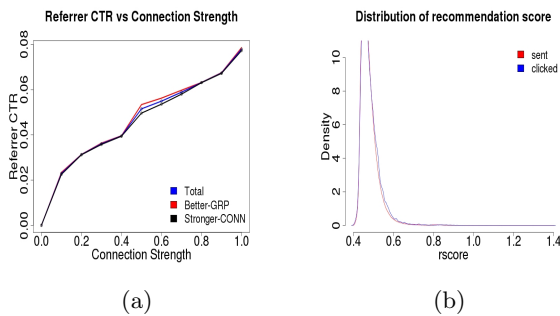


Figure 3: (a) Referrer CTR vs Connection Strength, (b) Distribution of Recommendation Scores Before and After Referral

6. CONCLUSIONS

Our main contributions in the paper are two folds. First, we presented *Social Referral*, a novel recommendation delivery mechanism which leverages a target user's social network for the effective delivery of relevant recommendations

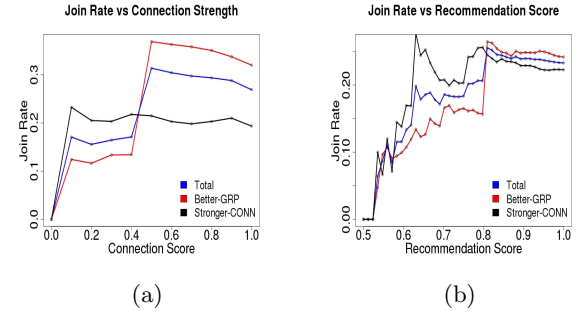


Figure 4: (a) Target User Join Rate vs Connection Strength, (b) Target User Join Rate vs Relevance

to the user. To our knowledge, most previous work has been focused on incorporating social network to improve recommendation relevance or explain recommendations. Little has been explored on leveraging social network for the delivery of recommendations. Second, we carried out a large scale user study with real world data that demonstrated the effectiveness of social referral. Our study showed that referrers are receptive to passing along recommendations to their network connections, and that recommendations delivered via social referrals are more than twice as likely to be accepted by target users than those directly delivered to them.

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