

Diffusion of Recommendation through a Trust Network

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Abstract

Several attempts have been made to analyze information diffusion on online knowledge sharing sites. In this poster, we report a preliminary study analyzing @cosme, a viral marketing site, which is among the largest community sites in Japan. The notable characteristics of @cosme are that users can bookmark their favorite reviewers; moreover, they can post their own reviews of products. In other words, a user puts trust in some other users for their reviews. This trust relation affects the opinions of users: A user refers to the ratings and opinions from the user's own favorite users when purchasing products; some users come to be trusted by a user based on mutual similarities of ratings and opinions. This bidirectional interaction between trust and opinion is an important phenomenon that elucidates consumer behaviors in online communities. In this paper, we describe an overview of the data in @cosme, analyses of recommendation through the trust relation, and concept for future analyses.

Keywords

viral marketing, trust network, recommendation

1. Introduction

Online social systems and knowledge sharing sites have received much attention as a medium of viral marketing. People write their experiences and opinions about products and services in their blogs and knowledge-sharing sites. Social relations among customers are analyzed in various ways [3, 2]. However, all social relations do not work equivalently: Users might *trust* someone more than others, and are consequently more influenced by that trusted person. Even if a certain user might make many recommendations, his influence is limited: Users do not trust such a person, and rarely become influenced.

Therefore, the question arises – How will a user come to trust others? The answer is suggested by recent studies of Golbeck et al. [1]. Similarity of profile attributes (such as ratings of movies) induces trust among people. In addition, trust can be inferred by other persons' trust.

In this poster, we propose a model of a trust network integrated with formation of users' opinions. The trust relation interacts with users' opinions as follows: i) a user puts trust in others *because* their opinions match to the user's opinion; and also ii) the opinion of a user is influenced by the opin-



Fig. 1: Screenshot of the top page at @cosme.

ions of other trusted users, *thus* the opinions will become similar. This bidirectional interaction of trust and opinion is an important perspective from which to analyze community behavior online.

We analyze a knowledge sharing site called @cosme¹. Since its opening in December 1999, @cosme has acquired a growing number of users. As of Fall 2005, it had a half a million registered users, 1.1 million visitors per month, and 115 million page-views. According to the operator (istyle Inc.), it is intended to be a “viral marketing” site for cosmetics [4]. Users of @cosme can post their reviews (called *Kuchikomi*) on cosmetic products on the system. Figure 1 shows the top page of the site. If a user finds another user's review interesting or useful, she can bookmark the reviewer as *Okiniiiri*. The reviewer is notified that she has a new fan. Because the system ranks users by the number of fans, some users are motivated to get more fans. We were provided the official user log data for more than five years, from December 1999 to April 2006.

2. Reviews and Bookmarks

Among the 4,310,346 reviews, 72,522 products have received at least one review: one product has received, on average,

¹ www.cosme.net

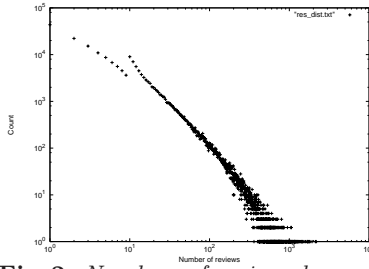


Fig. 2: Numbers of reviews by users.

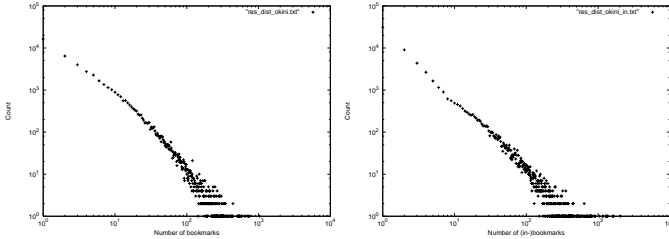


Fig. 3: Outdegree distribution of bookmarks.

Fig. 4: Indegree distribution of bookmarks.

59.4 reviews, which is quite a large number, reflecting the high activity among users in the community. On average, a user posts 6.43 reviews.

Figure 2 shows that the distribution of the number of reviews seemingly fits a power-law. We can see a strange gap between $x = 9$ and $x = 10$, which might result from the fact that a user with ten or more reviews can use a personalized recommendation function by the system, which apparently motivates users to post ten or more reviews. Figures 3 and 4 show the degree distributions when considering a bookmark as a directed edge. Both exhibit a linear relation on the log-log plots.

We can build a recommendation network that resembles that of Leskovec [2] using the two data sets: product review and user bookmark. Because a user registers a bookmark to check their latest reviews, we regard a review by bookmarked persons as a recommendation. If Alice has a bookmark to Betty, and Betty writes a review on product i at time t , then we infer that a recommendation from Betty to Alice on product i occurred at time t . Because @cosme allows a review only after a user purchases a product or at least has some experience using a product, we can regard a review as a proof of purchase.

We can draw a recommendation network on various products. Figure 6 is a network related to an eyelash curler with 182 nodes and 270 edges. The respective success rates of recommendations are 1.49% for this network. Figure 5 shows that the success rates of recommendations differ depending on the related items. Some items are likely to be successfully recommended; others are not.

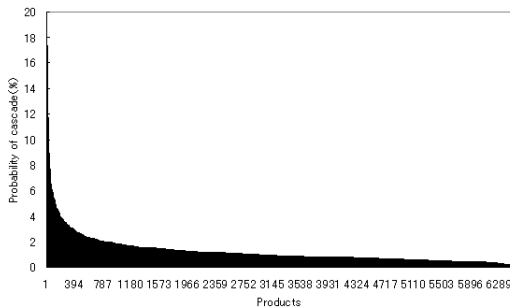


Fig. 5: Probability of recommendation on each item.

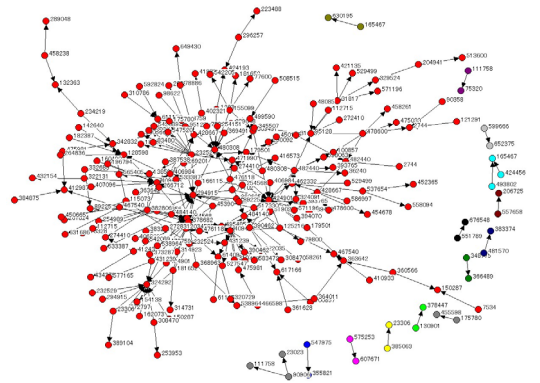


Fig. 6: Recommendation network for an eyelash curler. ($n = 182, e = 270$)

3. Trust and Recommendation

The probability of purchasing a product is influenced by the Okiniiri's reviews, and some products generate a cascade of recommendations. This result suggests to us the bidirectional interaction between trust and purchase behaviors. We model the interaction as follows. The rating of user x on product i , denoted as $s(x, i)$ ($0 \leq s(x, i) \leq 1$), is determined by the user's original evaluation $s_0(x, i)$ plus the rating of others whom user x trusts, denoted as $Trusted(x)$. $s(x, i) = \lambda s_0(x, i) + \frac{1-\lambda}{|Trusted(x)|} \sum_{y \in Trusted(x)} t(x, y) s(y, i)$. In that equation, $t(x, y)$ is the trust value $[0, 1]$ of user x to user y and λ is a constant between 0 and 1. In addition, the trust $t(x, y)$ is determined by the similarity of the rating between two users, and trust values from others. $t(x, y) = sim(\mathbf{s}(x, I), \mathbf{s}(y, I)) + \sum_{z \in Trusted(x) \& y \in Trusted(z)} t(x, z) \times t(z, y)$. Therein, I denotes a set of items, $\mathbf{s}(x, I)$ is the vector of rating on I , and $sim(\cdot)$ is the function to calculate similarity between two vectors. We use here the inner product and ignore the second term of the formula for simplicity.

After some transformations, we obtain $t(x, y) = (1/\mu) \times \left(\lambda \sum_{i \in I} s_0(x, i) s(y, i) + \frac{1-\lambda}{|Trusted(x)|} \sum_{i \in I} \sum_{z \in Trusted(x)} t(x, z) s(z, i) s(y, i) \right)$ where $\mu = 1 - \frac{1-\lambda}{|Trusted(x)|} \sum_{i \in I} s(y, i)^2$. This means that the trust of user x to user y is determined by the similarity of rating and also the similarity among neighbors of x and y . It is readily apparent that μ becomes large as $s(y, i)$ gets large, meaning that users with good ratings on many items might be less trusted.

In the future, we will validate this model of trust network dynamics empirically using the data on @cosme.

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