Community Gravity: Measuring Bidirectional Effects by Trust and Rating on Online Social Networks

Yutaka Matsuo
University of Tokyo
2-11-16 Yayoi, Bunkyo-ku
Tokyo, Japan
matsuo@biz-model.t.u-tokyo.ac.jp

Hikaru Yamamoto
Seikei University
3-3-1 Kichijoji Kitamachi, Musashino-shi
Tokyo, Japan 180-8633
yamamoto@econ.seikei.ac.jp

ABSTRACT

Several attempts have been made to analyze customer behavior on online E-commerce sites. Some studies particularly emphasize the social networks of customers. Users' *reviews* and *ratings* of a product exert effects on other consumers' purchasing behavior. Whether a user refers to other users' ratings depends on the *trust* accorded by a user to the reviewer. On the other hand, the trust that is felt by a user for another user correlates with the similarity of two users' ratings. This bidirectional interaction that involves trust and rating is an important aspect of understanding consumer behavior in online communities because it suggests clustering of similar users and the evolution of strong communities. This paper presents a theoretical model along with analyses of an actual online E-commerce site. We analyzed a large community site in Japan: *@cosme*. The noteworthy characteristics of @cosme are that users can bookmark their trusted users; in addition, they can post their own ratings of products, which facilitates our analyses of the ratings' bidirectional effects on trust and ratings. We describe an overview of the data in @cosme, analyses of effects from trust to rating and vice versa, and our proposition of a measure of of *community gravity*, which measures how strongly a user might be attracted to a community. Our study is based on the @cosme dataset in addition to the Epinions dataset. It elucidates important insights and proposes a potentially important measure for mining online social networks.

Categories and Subject Descriptors

J.4 [**Social and Behavioral Sciences**]: Sociology

General Terms

Algorithms, Human Factors

Keywords

Social networks, Online community, Trust, Rating

1. INTRODUCTION

Online social systems and knowledge-sharing sites have attracted much attention as viral marketing media. People share their experiences and opinions about products and services in their blogs and knowledge-sharing sites [1]. Many studies have undertaken analyses of opinions in the blogosphere [16, 2]. Regarding knowledge-sharing sites, relations among customers are analyzed in various ways. An early study by M. Richardson and P. Domingos provides a method to calculate a *network value* of online customers [20]. The network value of a customer is high when the customer is expected to influence other users' probabilities of purchasing the product both strongly and positively. Actually, D. Kemp et al. follow this problem using several widely studied models in social network analysis. The optimization problem of selecting the most influential customer is NP-hard. They provide a provable approximation for efficient algorithms [12]. A recent report describes techniques that decompose the reviews into segments that evaluate the individual characteristics of a product, such as image quality and battery life for a digital camera [4]. Revenue maximization (instead of influence maximization) is proposed and optional pricing strategies in social networks are discussed [11].

Information about customer experiences flows through social relations. Users share their experiences with their friends and colleagues. They might exchange that information with their friends online [22]. J. Leskovec et al. analyze recommendations among Amazon.com users [13]. Their results show how the recommendation network grows over time. Moreover, they describe its effectiveness from the viewpoints of the sender and the receiver of the recommendations.

Users might *trust* some people more than others, and might therefore be more influenced by them [6]. Even if a certain user might make many recommendations, such a person's influence is limited: Users neither *trust*, nor are they influenced by, such a person [13]. J. Golbeck et al. [8, 25] describe that the similarity of profile attributes (such as ratings of movies) induces trust among people. They analyzed data from FilmTrust, finding that several profile features beyond overall similarity affect the degree to which subjects trust other users. Another characteristic of trust is transitivity: If A trusts B, and B trusts C, then A can be inferred to trust C to some degree. The calculation is validated through experimental studies. Guha et al. develops a framework of a trust propagation scheme, and with it evaluates a large trust network using Epinions data. Their results show how trust and distrust exert considerable effects on trust propagation [10].

Considering those studies of the degree to which trust is formed, bidirectional effects on users' trust and ratings are readily apparent.

- *Rating to trust*: Users put trust in other members *because* their ratings match another user's ratings.

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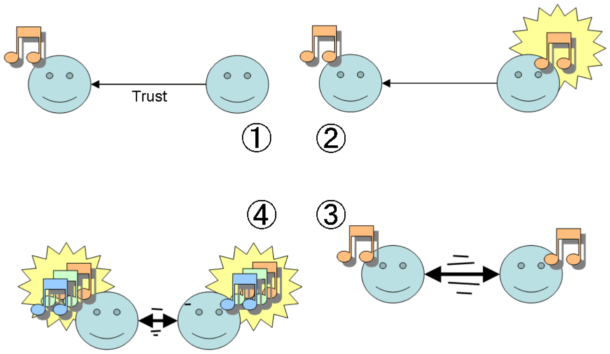


Figure 1: Sequential model of the trust effect and the homophily effect.

- *Trust to rating*: The rating of a user is influenced by the opinions of trusted others.

This bidirectional interaction of trust and opinion can be considered to be ubiquitous in the real world. People in similar cultures flock together: they are influenced by each other; moreover, they actively strive to make the culture unique. This phenomenon by which "similar" people gather is understood as *homophily* in the context of social network analysis [24, 18]. Singla and Richardson were able to discern a strong relation between who talks to whom on the instant messaging network, and what they search for, which is an illustrative example for understanding homophily's prevalence on the internet [21]. Online social media readily induce people to flock together. Consequently, the characteristics of this phenomenon are necessary for mining and analyzing online social communities.

Figure 1 depicts an illustration of bidirectional effects. In the first step, a user buys a product (shown as a music note) and another user is trusting her. She will adopt the product (in step 2), which will increase the homophily effect (in step 3). Then, the new product can easily diffuse between the two users.

As described in this paper, we analyze a knowledge-sharing site called *@cosme* (www.cosme.net). It is the largest online community site of "for-women" communities in Japan[1], and provides information and reviews related to cosmetic products. Notable characteristics of @cosme are that a user can register other users who can be trusted; she can also post reviews of products. The trusted users are called *Okiniiri* by her, which signifies a feeling of both favor and trust. Data of more than 700 thousand users gathered over five years enables us to analyze the bidirectional interaction of trust and opinions: (i) How does a user put trust in others from the similarity of ratings? (ii) What effects does that trust have on users' purchase behavior and ratings? We also conducted experiments on the Epinions dataset, which consists of both a trust network and user ratings of products. We designate the bidirectional effect as *community gravity* because it represents the power to induce users to the community. We believe that this analysis provides important insights for understanding various online social media.

The contributions of the paper are summarized as follows:

- The bidirectional effects of trust and opinions are analyzed both theoretically and empirically. Cosmetic products are a typical *experience good*. Therefore, other users' opinions in a community are useful for decision-making. The community gravity effect is observed.
- We propose a potentially useful measure to characterize a community. We identify a situation in which the online community becomes more clustered: trust and opinion have strong mutual effects.

[1]The site does not prohibit males, but 99% of the users are female.

The paper is organized as follows. In the next section, we provide an overview of the @cosme site. Then, we propose our model of trust and rating in Section 3. Experimental results are presented in Section 4, where two classification problems are addressed. After contrasting the results with those of the theoretical model, we propose a new measure for community gravity in Section 5. The network characteristics are described to underscore the effectiveness of that new measure. Finally, before concluding the paper, we present discussion of the results and implications.

2. OVERVIEW OF @COSME

2.1 Viral Marketing Site

Since its opening in December 1999, @cosme has acquired a growing number of users: as of Spring 2007, it had 825 thousand registered users, and 175 million page-views per month. According to the operator (istyle Inc.), it is intended to be a "viral marketing" site related to cosmetics.

Users of @cosme can post their reviews (called *Kuchikomi*) on cosmetic products (100,500 items of 11,000 brands) on the system. A review consists of a text describing the experience and the rating (from 1 (bad) to 7 (good)) of the product. We do not use text messages for this study; instead, we use a review and a rating interchangeably in this paper (when not confusing). Figure 2 portrays the top page of the site. A visitor can select a product and see reviews about it. She can also browse other products using the hierarchical classification of products or clicking reviewers' other reviews.

Once a user registers to the site, she becomes able to log in to the system. She is directed to a personalized page called "MyPage." News related to favorite brands and latest reviews announced by her trusted persons (Okiniiri) are shown. A user can bookmark the reviewer as Okiniiri if she finds someone's review trustworthy and useful. We use Okiniiri as a (directional) trust relation. The reviewer is notified that she has acquired a new user who registered her as Okiniiri; in other words, she has acquired a new *fan*. The system ranks users according to their respective quantities of fans. Apparently, some users are extremely motivated to accumulate more fans.

Figure 3(a) portrays the newly added reviews, new bookmarks, and new users for each month since the site's opening. The number of users has grown steadily, as have the numbers of trust relations and reviews.

2.2 Data overview

We were provided the official user log data for more than five years: December 1999 – April 2006. The data consist of the following three tables [2].

Product review (Kuchikomi) 4,310,346 records with user id, product id, date, and rating (1 (bad) – 7 (good)).

[2]The dataset is completely anonymized.

Figure 2: Screenshot of the top page at @cosme.

Trust relation (Okiniiri) 530,598 records with user id, (her trusted) user id, and date.

User profile 670,040 unique users with user id, registration and birth date, type of skin. These personal profiles are visible to others. *All* the users have their personal profiles, which are available for use in our analyses.

2.2.1 Product Reviews

We introduce some additional information related to the data. Among 4,310,346 reviews overall, 72,522 products have at least one review. Therefore, one product has, on average, 59.4 reviews, which is quite a large number, reflecting high activity among users in the community. About one-third of users have written at least one review. On average, a user posts 6.43 reviews. A user who posts at least once writes 20.47 reviews, on average.

Table 1 shows the most-reviewed products. Low-priced and commonly used products are listed higher, such as nail polish, cleansing oil, eye shadow, and lotion. The most active user (i.e., the user with the largest number of reviews) has posted 2179 reviews during the four years since 2002, which is about 1.5 reviews per day.

The distribution of the number of reviews apparently conforms to a power law, as depicted in Fig. 3(b). A strange gap separates $x = 9$ and $x = 10$, which might be attributable to the fact that a user with 10 or more reviews can use a personalized recommendation function by the system. This minimum requirement motivates users to post 10 or more reviews.

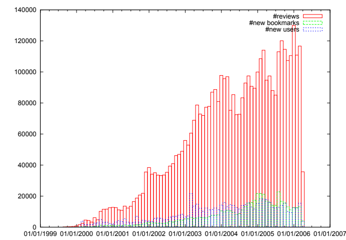
2.2.2 Trust Relation

The entire set of 530,598 trust relations comprises 49,685 users targeting 61,556 users. In other words, 7.4% of users use the bookmark function at least once, and 9.2% of users are trusted by others. On average, 10.7 trust relations are made by single users who have used the trust function at least once.

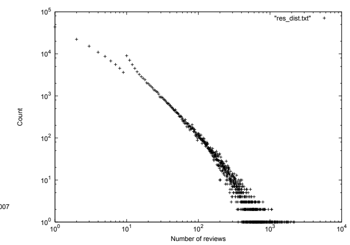
It is particularly interesting that the correlation between the number of fans and the number of her trusted users is not high: the Spearman correlation between the number of fans and the number of reviews is as high as 0.658, but that between the number of fans and the number of her trusted users is only 0.067. Figures 3(c) and 3(d) portray the degree distributions when considering a trust relation as a directed edge. Both exhibit a linear relation on log–log plots.

Table 1: Most-reviewed products.

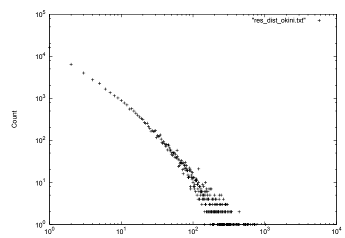
	#reviews	product name
1	18717	eyelash curler
2	16599	nail polish
3	15126	deep cleansing oil
4	12287	hair oil Ohshima Tsubaki
5	10877	cleansing oil
6	10508	eye shadow
7	10238	eyelash curler
8	10086	liquid foundation
9	9808	petroleum jelly
10	9570	skin conditioner



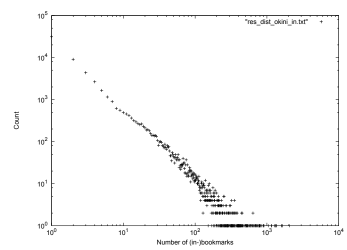
(a) Numbers of new users, new bookmarks, and new reviews per month.



(b) Numbers of reviews by users and their counts.



(c) Outdegree distribution of bookmarks.



(d) Indegree distribution of bookmarks.

Figure 3: Overview of the network data on @cosme

3. THEORY

Bidirectional interaction of trust and rating can be understood as follows: In the first step, a user buys a cosmetic product and another user is trusting her. She will adopt the product, which will increase the homophily effect. Then, the new product can easily diffuse between the two users.

Figure 4 portrays a community with strong gravity if we examine phenomena on a community scale. A product is diffused through the trust network, which will result in more tightly connected community. Consequently, the new product can easily diffuse within the community, which will strengthen the community further. A user will be induced to join the community if she is connected to the community. This effect resembles gravitational force. For that reason, we designate it as *community gravity* in this paper.

If no bidirectional effects pertain in the community, the

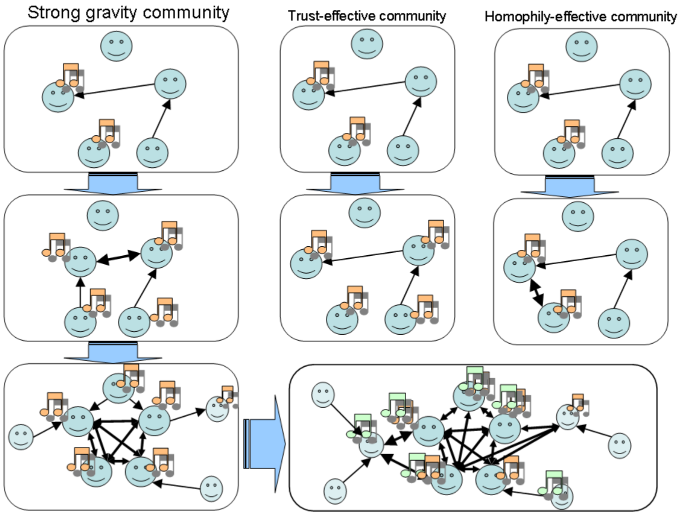


Figure 4: Strong gravity community vs. other communities.

interaction is simpler. In Fig. 4, the interaction of a trust-effective community is shown: a product can be diffused well through the trust network. Another product might be diffused similarly, but no cumulative effect occurs. On the other hand, in the homophily effective community, similar users will share mutual trust. However, unless a trust relation has an effect on the diffusion of a product, a product neither diffuses through the network, nor does the community become stronger. Therefore, to understand the community dynamics, it is important to consider effects from trust to rating and vice versa.

First, to show how a community grows with strong community gravity, we model the interaction between rating of a product and trust relation. The rating of user x on product i at time t, denoted as $s_{x,i}(t)$ $(0 \leq s_{x,i}(t) \leq 1)$, is fundamentally determined by the preference of user x to product i. It is also influenced by the rating of other users that user x trusts. Therefore, we model the rating as the summation of her original evaluation $s_{x,i}(0)$ and the ratings of users she trusts. We denote the users who are trusted by user x as N_x.

$$s_{x,i}(t+1) = \lambda_0 s_{x,i}(t) + \lambda_1 \frac{1}{|N_x(t)|} \sum_{y \in N_x(t)} t_{x,y}(t) s_{y,i}(t) \quad (1)$$

In the equation presented above, $t_{x,y}(t)$ represents the trust value [0,1] of user x to user y at time t and λ_0 and λ_1 are constants. We divide the rating of trusted users by the number of her trusted users $|N_x(t)|$, thereby taking the average of ratings. (Otherwise, if a user trusts more users, her original evaluation is less weighted, which seems unreasonable.) We can write the expression in a more general form as

$$\mathbf{S_{t+1}} = \lambda_0 \mathbf{S_t} + \lambda_1 \mathbf{T_t} \mathbf{S_t} = (\lambda_0 \mathbf{I} + \lambda_1 \mathbf{T_t}) \mathbf{S_t}$$

where $\mathbf{S_t} = \{s_{x,i}(t)\}$ and $\mathbf{T_t} = \{t_{x,y}(t)/|N_x(t)|\}$.

Second, we model the trust relation of a user to another user based on the similarity of ratings. As described in [9], trust is induced by the similarity of ratings between two users.

$$t_{x,y}(t+1) = \mu_0 t_{x,y}(t) + \mu_1 sim(\boldsymbol{s}_{x,I}(t), \boldsymbol{s}_{y,I}(t)) \quad (2)$$

Therein, $t_{x,y}(0)$ is the original trust from user x to user y. A set of items is denoted as I, and $\boldsymbol{s}_{x,I}(t)$ is the vector of rating $s_{x,i}(t)$ $(i \in I)$. A function $sim(\cdot)$ is used to calculate the similarity between two vectors (e.g., cosine similarity and inner product), and μ_0 and μ_1 are constants[3]. We can also write the expression using matrices, as

$$\mathbf{T}_{t+1} = \mu_0 \mathbf{T}_t + \mu_1 \mathbf{S}_t^T \mathbf{X} \mathbf{S}_t,$$

where $\mathbf{X}$ is a (Mahalonobis distance) matrix to calculate the distance. Below we use an inner product as a similarity measure for simplicity. As described later, cosine similarity functions well as a similarity measure. The inner product corresponds to cosine similarity if we assume that the vector s is normalized so that the vector length would be 1.

Formula 1 and Formula 2 are mutually dependent. If we solve the two formulae, we can obtain[4]

$$t_{x,y}(t+1) = \frac{1}{K_{xy}(t)} \frac{\mu_1 \lambda_1}{|N_x(t)|} \left(\sum_{z \in N_x(t), z \neq y} t_{x,z}(t) s_{y,i}(t) s_{z,i}(t) \right),$$

where

$$K_{xy}(t) = 1 - \frac{\mu_1 \lambda_1}{|N_x(t)|} \sum_{i \in I} s_{y,i}(t)^2.$$

This formula shows that the trust of user x to user y is determined by the similarity of the rating and also the similarity among y to the other users. It is apparent that K_{xy} becomes large if $s(y,i)$ gets large, meaning that users with good ratings on many items might be less trusted.

Similarly, we can obtain

$$s_{x,i}(t+1) = \frac{1}{K_{xy}(x)} \frac{\mu_1 \lambda_1^2}{|N_x(t)|^2} \sum_{y \in N_x(t)} \sum_{z \in N_x(t) z \neq y} t_{x,z}(t) s_{y,i}(t)^2 s_{z,i}(t).$$

This formula is complex, but we can understand it as follows: we assume that user x increases her rating on product i with Δs_{xi}. Then, $t_{x,y}$ increases by $\mu_1 \Delta s_{xi} s_{y,i}$; if user y has a high rating on product i, the increase on $s_{x,i}$ increases the similarity, resulting in the increase of trust $t_{x,y}$. If user y has a low (or zero) rating on product i, it does not bring much of an increase (sometimes even a decrease) of $t_{x,y}$[5]. Eventually, $s_{x,i}(t)$ is increased by

$$\frac{\lambda_1 \mu_1}{|N_x|} \Delta s_{xi} s_{y,i}(t)^2. \quad (3)$$

Therefore, an increase of rating $s_{x,i}$ again brings the increase of rating $s_{x,i}$ itself by order of $\lambda_1 \mu_1 s(y,i)^2/|N_x(t)|$ through neighboring user y. The user eventually obtains a higher increase on $s_{x,i}(t)$ if user x has many neighbors with a high

[3]Trust can also be induced in a transitive manner using the trust values of more distantly related users, as described in a previous study [9, 10]. However, because similarity measures usually have some transitivity, we use no explicit formulation of transitive trust.

[4]Here for simplicity, we assume that $t_{x,y}(0) = 0$ and $s_{x,i}(0) = 0$. Complete formulae will be found in the longer version of the paper.

[5]Because we assume s to be normalized, in the case for which $s_{y,i}(t)$ is low, $t_{x,y}(t)$ actually decreases.

rating on product i. In this way, the ratings of users become similar if they are closely connected, thereby producing a cluster of users with similar preferences.

Depending on product and user characteristics, λ_1 and μ_1 differ. The opinions of users on a particular product tend to be similar locally, which produces denser clusters than those for other products.

4. DATA ANALYSIS

For the discussion presented in this section, we take a practical approach to analyze bidirectional interaction between trust and rating. By empirically examining each interaction, we can support the model of the previous section.

We build two prediction problems: prediction for trust and prediction for rating of the product. Trust prediction is, given two users x and y, to predict whether a trust relation from x to y exists. It can be considered as a link prediction problem [7]. We use the features based on two users' profiles, product ratings, and other trust relations.

Rating prediction is complementary: given a user and a product, we seek to predict the rating. Features are generated using her profile, her ratings of the other product, then her trusted users. Both problem resolutions produce a prediction based on the data before the time point. Models to predict trust and ratings are learned using classification algorithms.

4.1 Trust Prediction

4.1.1 Features

To predict the trust from user x to user y, we use features of three kinds: each corresponds to a table in @cosme data. The overall features are presented in Table 2. The first type of feature is based on a profile table; we use the properties of user x and user y, along with the properties' difference and correspondence.

The second type of feature uses the product-review table. The features are invented to measure the similarities of ratings of user x and user y on various products. For example if user x announces ratings on five products, then $\{(P_1, 6), (P_2, 4), (P_3, 5), (P_4, 2), (P_5, 7)\}$, where P_i represents product i annotated using a rating of an integer [1,7]. Assume that user y makes ratings of four products: $\{(P_1, 5)$, $(P_2, 5)$, $(P_6, 7)$, $(P_6, 3)\}$. Then, we can calculate the similarity using various measures. In this case, P_1, P_2, and P_5 are rated by both users. Therefore, the *matching coefficient* is three. The value is $3/\sqrt{4}\sqrt{5} = 0.67$ if we perform calculations using cosine similarity, denoting a set of items rated by user x as I_x. The three measures we use are the following:

(i) Matching coefficient: $|I(x) \cap I(y)|$,

(ii) Cosine similarity: $|I(x) \cap I(y)|/(|I(x)||I(y)|)$, and

(iii) Jaccard coefficient: $|I(x) \cap I(y)|/|I(x) \cup I(y)|$.

We also use (iv), a product for which $I(x)$ is considered as a vector, and calculate $I(x) \cdot I(y)$.

Users might refer to reviews with good ratings more often, or reviews with a bad rating more often. Therefore, we define a set of items with good/bad reviews as $I_{good}(x)$ and $I_{bad}(x)$ correspondingly. We define a good rating as one with a score of 6 points or more; a bad rating has 2 points or less. In the example, user x assigns a good rating on P_1 and P_5, whereas user y assigns a good rating to P_7. Then, we can define the overlap of $I_{good}(x)$ and $I_{good}(y)$, or $I_{bad}(x)$ and $I_{bad}(y)$ as well.

Users might not be familiar with a product. However, sometimes they make a purchase decision based on a brand or manufacturer. Users often have several preferred brands or manufacturers. Therefore, we can calculate the overlap of rated items as categorized by brands, or as categorized by manufacturers. Overall, we have 4 (#measures) × 3 (#sets) × 3 (product/brand/manufacturer) = 36 features.

The third type of feature is derived from trust relations (except the very relation from x to y, which we seek to predict). Following the link prediction study [15], we build the following attributes: (i) the number of neighbors for user x and y, (ii) distance on the network, (iii) common neighbors of user x and user y, (iv) Jaccard coefficient of neighbors of user x and y, (v) Adamic–Adar, which is defined as $\sum_{z \in N_x \cap N_y} \frac{1}{\log |N(z|}$, and (vi) preferential attachment, defined as $|N_x||N_y|$. The trust network comprises trust relations of both directions (where we regard the trust relation from x to y as identical to trust relation from y to x), single relations (where we distinguish the relation from x to y and the relation from y to x), and reciprocal relations (where we put a link from x to y if a trust relation from user y to user x exists). Therefore, we have three networks associated with respective features.

4.1.2 Results

We randomly chose 1000 pairs of users with trust relations and another 1000 pairs of unrelated users without relations; they correspond respectively to positive and negative sets. We used a support vector machine (SVM) with a linear kernel [23] as a classifier[6].

Table 4 shows the performances of classifying trust relations. Each group of attributes contributes to the classification. Trust features and ratings features contribute greatly to the performance compared to profile features. The F1 value is 82.46% if we use all three groups.

Table 5 shows features with the highest weights in the obtained model by the SVM classifier. It is apparent that the number of trusted users for y and the number of trusted users by x are the two highest features, which might be readily apparent. Highly trusted users are likely to be trusted using a particular user; a user who trusts many others is likely to trust another.

Some features in the table are of particular interest: `Jaccard-directional` is the overlap of user x's trusted users and trusted users by user y, which implies the transitivity of trust relations. The `all-product-cos` is the similarity of all rated items by user x and those by user y. This can be understood that the similarity can be well measured using the cosine of the rated product.

4.2 Rating Prediction

Next, we build the rating prediction problem. The features we used, as presented in Table 3, are categorized into profile, rating, and trust, as well as trust prediction.

Considering the rating by user x of product i, the profile features are simply the properties of user x. The rating features are the number of ratings by user x, the average

[6]We compared it to several other classifiers including J4.8 and Naive Bayes. They produced similar results overall. The results worsen by a few points.

Table 2: Features for trust prediction (from user X to user Y).

Group	type	features
Profile	skin	skin-same (binary), skin-X (category), skin-Y (category)
	profession	profession-same (binary), profession-X (category), profession-Y (category)
	age	age-X, age-Y, age-dif
	history	history-X, history-Y, history-dif
Rating	good rating	good-product-matching, good-product-product, good-product-cos, good-product-Jaccard, good-brand-matching good-brand-product, good-brand-cos, good-brand-Jaccard, good-manufacturer-matching, good-manufacturer-product, good-manufacturer-cos, good-manufacturer-Jaccard
	bad rating	bad-product-matching, bad-product-product, bad-product-cos, bad-product-Jaccard, bad-brand-matching, bad-brand-product, bad-brand-cos, bad-brand-Jaccard, bad-manufacturer-matching, bad-manufacturer-product, bad-manufacturer-cos, bad-manufacturer-Jaccard
	all rating	all-product-matching, all-product-product, all-product-cos, all-product-Jaccard, all-brand-matching, all-brand-product, all-brand-cos, all-brand-Jaccard, all-manufacturer-matching, all-manufacturer-product, all-manufacturer-cos, all-manufacturer-Jaccard
	stats	review-n-X, rating-ave-X, rating-std-X, review-n-year-X, popularity-X, over6-X, under2-X, review-n-Y, rating-ave-Y, rating-std-Y, review-n-year-Y, popularity-Y, over6-Y, under2-Y
Trust	stats	trusted-n-X, trusting-n-X, trusted-n-Y, trusting-n-Y
	graph	distance
	similarity	common-neighbors-directional, common-neighbors-reverse, common-neighbors-undirectional, Jaccard-directional, Jaccard-reverse, Jaccard-both, Adamic–Adar-directional, Adamic–Adar-reverse, Adamic–Adar-undirectional, preferential-directional, preferential-reverse, preferential-undirectional

Note: All features are continuous (except some profile features). We were not able to explain all the features, but we did explain some: The `skin-same` is 1 when the skin types of two users are the same. The `age-dif` is the difference of ages (days after the birthday) of two users. The `good-product-matching` means the matching coefficient of reviews with good rating (6 or more score). The `review-n-X` means the number of reviews by user X. The `over6-Y` is the number of good ratings (score of 6 or more) by user Y. The `trusted-n-X` is the number of users whom user X trusts. The `trusting-n-Y` is the number of users who trust user Y. The `Adamic-Adar-directional` means the similarity within the directional trust network measured using the Adamic–Adar index.

Table 4: Performance of trust prediction.

Attributes	Precision	Recall	F1
Profile	54.89%	53.18%	54.02%
Rating	77.38%	65.29%	70.82%
Trust	90.04%	71.33%	79.60%
Profile + Rating	77.55%	67.41%	72.12%
Profile + Trust	89.78%	72.30%	80.10%
Rating + Trust	88.73%	75.52%	81.60%
All	88.10%	77.51%	82.46%

of ratings by user x, the standard deviation of the ratings by user x, the number of good ratings, and the number of bad ratings. We also calculate these values for brands and manufacturers. Then we produce summations of ratings on product i: the number of reviews, the average and standard deviation of ratings, and so on.

As for the trust relation, we aggregate the ratings by users who are trusted by user x. The number of ratings, the average of ratings, and the standard deviation are calculated to the product, the brand, and the manufacturer.

The rating prediction is reduced to classification. The task is to classify a review into a good review class (with 6 points or more) and a non-good review class (with 5 points or less). The results are presented in Table 6. It is apparent that ratings of features and trust features have comparable performance. In addition, $F1$ is 86.8% using SVM if we use all the features.

The highly weighted features are presented in Table 7. It is apparent that the number of reviews of products and the number of reviews by the user are important features. Particularly interesting features include `user-brand-ave` and

Table 5: Highly weighted features in trust prediction.

1	trusting-n-Y	5.6075
2	trusted-n-X	5.3342
3	Jaccard-undirectional	3.8225
4	Jaccard-directional	3.7014
5	all-product-cos	2.8291
6	Jaccard-reverse	2.6943
7	Adamic–Adar-directional	1.7409
8	common-neighbors-directional	1.5182
9	all-product-Jaccard	1.4858
10	review-n-Y	1.1943
11	common-neighbors-undirectional	1.1883
12	bad-product-cos	-1.1712
13	over6-X	-1.0746
14	bad-product-Jaccard	-1.0309
15	popularity-X	-1.0119

`okiniiri-rate-ave`. A user has favorite brands. For that reason, the average of ratings of the brand is a good feature. The average of ratings of users whom the user trusts is also a good feature, justifying the effect of trusted users in Formula 1.

4.3 Estimating Parameters

To investigate the correspondence between the practical classifiers and the evolution model in the previous section, we select a few highly weighted features that represent respective terms in the theoretical formulae. Subsequently, we apply regression using SVM using the features to estimate parameters μ_1 and λ_1.

Table 3: Features for rating prediction (by user X for product A)

Group	type	features
Profile		skin-X (category), profession-X (category), age-X, history-X
Rating	user stat	user-total-n, user-total-ave, user-total-std, user-total-over6, user-total-under2, user-oldest-review, user-latest-review
	user	user-brand-n, user-brand-ave, user-brand-std, user-brand-over6, user-brand-under2, user-manufacturer-n, user-manufacturer-ave, user-manufacturer-std, user-manufacturer-over6, user-manufacturer-under2
	product	product-review-n, product-review-ave, product-review-std, product-review-over6, product-review-under2, product-oldest-review, product-latest-review
	brand	brand-review-n, brand-review-ave, brand-review-std, brand-review-over6, brand-review-under2
	manufacturer	manufacturer-review-n, manufacturer-review-ave, manufacturer-review-std, manufacturer-review-over6, manufacturer-review-under2,
Trust	product	trusted-review-n, trusted-rate-ave, trusted-rate-std, trusted-over6, trusted-under2
	brand	trusted-brand-review-n, trusted-brand-rate-ave, trusted-brand-rate-std, trusted-brand-over6, trusted-brand-under2
	manufacturer	trusted-manufacturer-review-n, trusted-manufacturer-rate-ave, trusted-manufacturer-rate-std, trusted-manufacturer-over6, trusted-manufacturer-under2

We explain some features hereinafter. The `user-total-n` is the number of reviews by user X. The `user-total-ave` and `user-total-std` respectively signify the average and standard deviation of the ratings by user X. The `user-latest-review` is the number of days after the latest review is posted by user x. The `user-manufacturer-n` is the number of reviews by user X of products made by the same manufacturer of product A. The `product-review-under2` is the number of ratings with a score of 2 or less on product A. The `brand-review-ave` is the average rating of products with the same brand as product A. The `trusted-review-n` is the number of reviews posted by users who are trusted by user A. The `trusted-brand-ave` is the average rating of the brand of product A by users who are trusted by user X.

Table 6: Performance of rating prediction.

Attributes	Precision	Recall	F1
Profile	53.14%	64.36%	58.21%
Rating	89.34%	79.73%	84.26%
Trust	83.27%	46.39%	59.59%
Profile + Rating	89.32%	79.62%	84.19%
Profile + Trust	81.77%	46.86%	59.58%
Rating + Trust	90.01%	83.76%	86.77%
All	89.85%	81.85%	85.66%

For trust prediction, by selecting four highly weighted features and applying regression, we can obtain the following formula.

$$\begin{aligned} t_{x,y}(t+1) &= \mu_0 t_{x,y}(t) + \mu_1 sim(\boldsymbol{s}_{x,I}(t), \boldsymbol{s}_{y,I}(t)) \\ &\sim 0.34 \times \texttt{trusting\_n\_Y} + 0.31 \times \texttt{trusting\_n\_X} \\ &\quad +0.25 \times \texttt{Jaccard\_directional} \\ &\quad +0.09 \times \texttt{all\_product\_cos} \end{aligned} \tag{4}$$

The first three terms can be attributed to $t_{x,y}(t)$. We can estimate μ_1 as 0.09 if we take `all-product-cos` as a similarity measure.

Regarding rating prediction, by selecting four highly weighted features, we can construct the following model.

$$\begin{aligned} s_{x,i}(t+1) &= \lambda_0 s_{x,i}(t) + \lambda_1 \frac{1}{N_x} \sum_{y \in \mathrm{Trusted}_x} t_{x,y}(t) s_{y,i}(t) \\ &\sim 0.27 \times \texttt{user\_total\_n} + 0.42 \times \texttt{product\_review\_n} \\ &\quad +0.16 \times \texttt{user\_brand\_ave} \\ &\quad +0.14 \times \texttt{trusted\_rate\_ave} \end{aligned} \tag{5}$$

Similarly, the first three terms are attributed to $s_{x,i}(t)$. By selecting `trusted-rate-ave` as a rating measure, we can estimate λ_1 as 0.14.

Table 7: Highly weighted features in rating prediction.

1	product-review-n	4.5135
2	product-review-over6	3.8816
3	user-total-n	2.5622
4	product-latest-review	-2.075
5	product-review-under2	1.8962
6	user-brand-ave	1.706
7	trusted-rate-ave	1.6909
8	trusted-under2	1.5926
9	trusted-brand-review-n	-1.4693
10	user-manufacturer-ave	1.4477
11	user-total-over6	1.2228
12	user-manufacturer-n	1.0543
13	brand-review-std	-1.0429
14	trusted-manufacturer-review-n	-1.0241
15	trusted-review-n	1.015

5. COMMUNITY GRAVITY

5.1 Measuring Bidirectional Effect

For the analysis described above, we can infer that $\mu_0 = 0.09$ and $\lambda_1 = 0.14$ for overall users and products in @cosme. However, this value varies depending on the product. Some products, brands, and manufacturers might have a large μ_0 and λ_1, i.e., strong community gravity. Especially, from a marketing perspective, when a brand has a large bidirectional effect, it generates a strong community: users become more connected, and a new product prevails easily in the community. Each cosmetics manufacturer strives to establish and strengthen its own brands. Therefore, it is reasonable to consider a brand as an important medium of the bidirectional effects. Below, we present analyses of the bidirectional effect, particularly addressing cosmetics brands.

The parameters μ_1 and λ_1 can be estimated for each

Table 8: List of brands with the highest CG measure.

CG	brand	manufacturer
0.142	Majolica Majorca	Shiseido
0.131	Chanel	Chanel
0.122	Yves Saint Laurent	Yves Saint Laurent Parfums
0.0997	Anna Sui Cosmetics	Anna Sui Cosmetics
0.0963	Kate	Kanebo
0.0745	Esfield	Esfield
0.0741	Lush	Lush
0.0729	Baby Pink	Bison
0.0728	Guerlain,	Guerlain
0.0713	Canmake	Ida Laboratories

brand: In Formula 4, the variable `all-product-cos` is calculated for all products of the target brand. Regarding Formula 5, the variables `product-review-n`, `user-brand-ave`, and `trusted-rate-ave` are calculated using all products of the brand. In this manner, we can estimate μ_1 and λ_1 for each brand b, denoted as $\mu_1(b)$ and $\lambda_1(b)$.

To measure the strength of a brand based on the bidirectional interaction model, we propose a new index, called *community gravity (CG)*. The index is defined for a set of items, which in this case corresponds to a brand. It incorporates effects from trust to rating, and from rating to trust, as follows.

$$CG(b) = \mu_1(b) \times \lambda_1(b)$$

Because the user's rating increases in a reflective manner in direct relation to $\mu_1\lambda_1$, as shown in Formula 3, this measure represents a fundamental value of the brand characteristics.

Table 8 portrays products with high CG values. It is apparent that some major brands have high CG values. For example, Majolica Majorca is Shiseido's make-up brand for young consumers with a strong personality. Users of Lush and Anna Sui cosmetics are known to have extremely high brand loyalty. Consequently, high CG implies that the brand is strong because it can create strong user communities.

5.2 Product Propagation Network

To clarify the characteristics of CG measure further, we attempt to investigate the difference of user behavior depending on different CG values.

We can build a propagation network resembling Leskovec's recommendation network [13] using product reviews and trust relations. We regard a review by trusted persons as a recommendation. If Alice registers Betty as trusted, and Betty puts a good rating on product i at time t, then we regard it as a recommendation from Betty to Alice on product i that occurred at time t. Because @cosme permits a review only after a user purchases or tries a product, we can regard a review as proof of purchase: in other words, we can confidently infer that Alice bought i before time t if Alice has a review on product i at time t.

Then we can define the success of propagation as follows: If Alice receives a recommendation on product x from Betty at time t_1, and if Alice writes a (first) review on product i at time t_2, where $t_1 < t_2 < t_1 + T$[7], then we consider that the recommendation is successful. We can draw a propagation network for various products. Figure 6 portrays the

[7] We set T as 180 days.

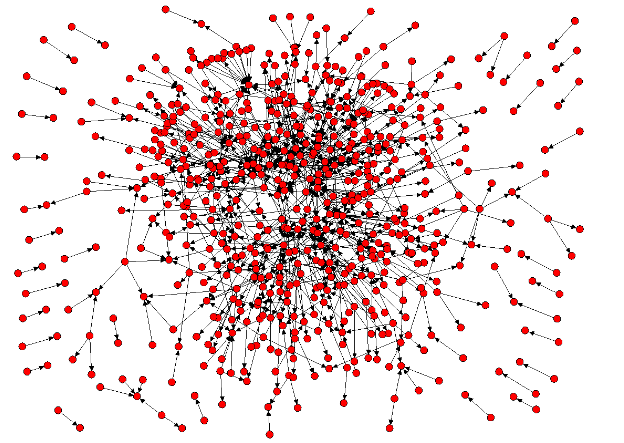


Figure 5: Propagation network for an eyelash expander of the highest-CG brand. ($n = 630, e = 858$, **where n is the number of nodes and e is the number of edges.**)

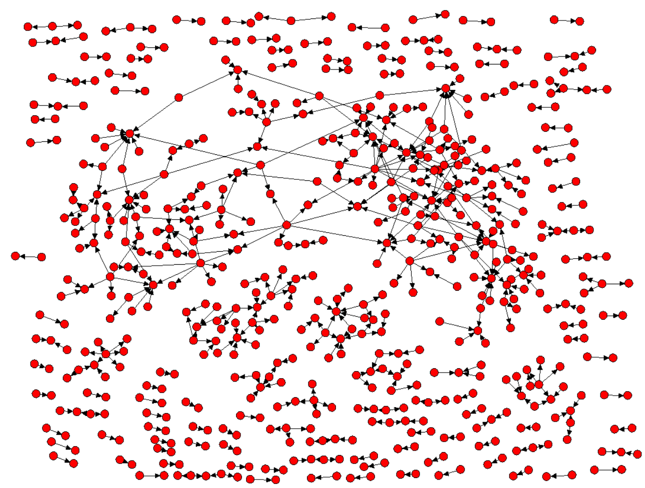


Figure 6: Propagation network for a lotion with the most popular brand (but with low CG). ($n = 581, e = 496$)

(success) propagation network on a Majolica Majorca eyelash expander, which has the highest CG. The nodes are users and the (directed) edges are the success propagations between two users. A core group of users who are mutually connected by dense relations is readily apparent. These users diffuse the product to more peripheral users. On the other hand, Figs. 5 display the network for a lotion of DHC, which is the most popular brand with numerous product reviews, although the CG value is low (in the 83rd place). Although they have almost equal quantities of nodes and edges, this network is flatter than that of Majolica Majorca. Those users do not produce big clusters. Success rates of the propagations are 1.82% and 0.47% for these two networks.

We present a scatter plot of the recommendation success rate and the CG value for popular brands in Fig. 7. Using the plot, we can assess the correlation of these two values. In summary, the CG measure is a good index to represent a user's bidirectional effects on trust and rating. A high CG value implies the power of the brand to produce strong user communities.

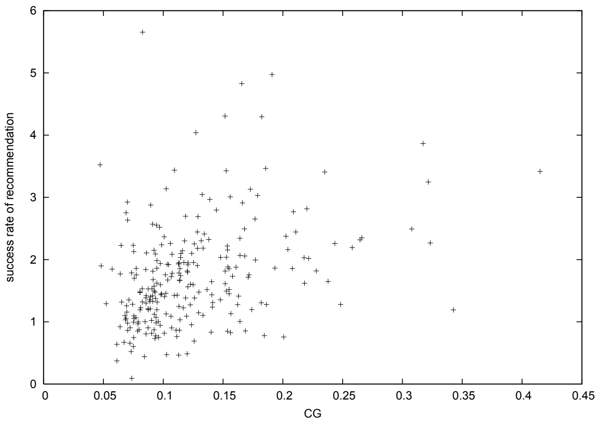


Figure 7: Plot of CG and the recommendation success rate.

6. DISCUSSION

6.1 Static Model

We must describe the evolution model of trust and rating in Section 3. Alternatively, we can consider a static model with which data analysis can be done easily. Below we describe the model briefly.

Assuming that we have two matrices $\mathbf{S}$ and $\mathbf{T}$, then $\mathbf{S}$ is an $n \times n$ trust matrix, representing who trusts whom. In addition, $\mathbf{T}$ is an $n \times m$ rating matrix, representing one's rating for each product. Then we can calculate the bidirectional effect using the matrices on a (set of) products.

We denote $trust_{x,y}$ if user x has trust with user y, and $rate_{x,i}$ if user x rated product i high. Then the probability to rate product i is represented as $P(rate_{y,i}|trust_{y,x}, rate_{x,i})$, and the ratio to $P(rate_{y,i}|rate_{x,i})$ can be an index to represent the degree to which trust affects the ratings.

In contrast, the probability for user x to trust user y based on purchased products is represented as $P(trust_{y,x}|rate_{y,i}, rate_{x,i})$, which can be compared with $P(trust_{y,x})$. Consequently, both effects can be an index by multiplying two figures as[8]

$$\frac{P(rate_{y,i}|trust_{y,x}, rate_{x,i})}{P(rate_{y,i}|rate_{x,i})} \cdot \frac{P(trust_{y,x}|rate_{y,i}, rate_{x,i})}{P(trust_{y,x})}$$
$$= \left\{ \frac{P(trust_{y,x}, rate_{y,i}, rate_{x,i})}{P(trust_{y,x})P(rate_{y,i}, rate_{x,i})} \right\}^2$$

The denominator is calculable by counting non-zero values in $\mathbf{T}$ and the number of non-zero values in $\mathbf{SS^T}$. Therefore, the bidirectional effect on product i can be approximated using the two matrices $\mathbf{T_t}$ and $\mathbf{S_t}$. This model can be considered as a simple variant (discarding the evolution aspect) of the community gravity measure described in Section 5. However, because the evolutionary aspect is important to understand community behavior, we adopt the evolution model in this paper.

6.2 Analysis of the Epinions dataset

Our algorithm is applicable if we have trust data (among users) and rating data. We also conducted analysis of the dataset of Epinions, which is a website where people can review products.

[8]We assume that $P(trust_{y,x}|rate_{x,i}) = P(trust_{y,x})$. In this static model, the time of purchase and trust is discarded.

Table 9: Performance of trust prediction (Epinion dataset).

Attributes	Precision	Recall	F1
Rating	79.75%	74.12%	76.83%
Trust	96.72%	69.41%	80.82%
Rating + Trust	92.21%	86.03%	89.01%

Table 10: Performance of rating prediction (Epinion dataset).

Attributes	Precision	Recall	F1
Rating	78.11%	63.89%	70.69%
Trust	57.57%	83.61%	68.19%
Rating + Trust	72.61%	7769.%	75.07%

We used the extended Epinions dataset[9], which contains about 132,000 users and 840,000 trust statements, to conduct the same experiment. Figures 9 and 10 present results of trust prediction and rating prediction, as we have done with the @cosme dataset. The Epinions dataset does not include user profiles. For that reason, we cannot use the attributes derived from user profiles.

Both the rating and trust information are important for the performance. Particularly, `Jaccard-undirectional`, `Jaccard-directional`, `trusting-n-X`, and `trusted-n-Y` are the useful features for trust prediction, and `user-total-n`, `user-total-over4`, `trusted-review-n`, and `product-review-n` are useful features for rating prediction. Overall, the tendency resembles that of the @cosme dataset very well, which is evidence of the robustness of our algorithm.

The algorithm might be applicable to online shopping sites (such as Amazon.com, Epinions, and eBay) if we were able to use trust (or bookmarking) data. We show that a small number of instances of expressed trust per individual enables us to predict trust between any two people in the system with high accuracy. The development of social networking services might enable the use of social network data at online shopping sites, thereby providing the opportunity to use our algorithm to elucidate the bidirectional effects of products. Our algorithm is also applicable to existing data of several types: e.g., published data (e.g. DBLP, Citeseer, and Cora database) have information about papers presented at conferences (which corresponds to purchase of a product), and the co-authorship of a paper or co-affiliation to an institute (which corresponds to trust in a person). Consequently, the brand value of a conference, a journal, or an academic field is measurable.

7. RELATED WORK

Numerous attempts have been undertaken to investigate brand communities in the marketing science field. For example, Brown et al. compare members and non-members of virtual communities and report that the community members are more likely to engage in online shopping and have higher propensity to re-visit the website [5]. Muniz and O'Guinn expand the traditional model of "customer-brand" relation to a "customer-brand-customer" triad [19]. The results of field research and in-depth interviews reflect that the brand community is a powerful tool to strengthen brand loyalty. McAlexander, Schouten, and Koenig also describe the impact of brand community [17]. They show that customers who purchase a branded product "often do so with

[9]Data are available from www.trustlet.org/wiki/Extended_Epinions_dataset.

the support of other users, which engenders the possibility of brand-focused interpersonal bonds." Forman et al. report a relation between reviews and sales from the identity disclosure perspective [6]. Our study is inspired by these findings, which have provided a general model to explain the emergence and strength of brand communities.

Recently, evolution models of social networks have received much attention: J. Leskovec et al. develop a model of network evolution using four large datasets: Flickr, Delicious, Yahoo! Answers, and LinkedIn [14]. Anagnostopoulos et al. define the general models of social correlation [3]. Causes of correlation in social networks are categorizable into influence, homophily, and environment. They used the Flickr dataset and analyzed the effects. Our research shares a similar motivation with those studies: we also seek a model of the interaction and evolvement of social networks.

8. CONCLUSION

As described in this paper, we have explained community gravity, which is the bidirectional effect of trust and rating both theoretically and empirically, using data found on a viral marketing site @cosme. We first described the model in Section 3. Numerous methods might be used to produce the features used in the model. Therefore, we make trust prediction and rating prediction problems in Section 4. By solving the problems, we can identify good features that are useful in the model. Community gravity is defined and measured in Section 5; we show brands with strong CG values. The community gravity is also observed by investigating product propagation networks, where a product with high CG value can be diffused easily through the network. Depending on the product, this bidirectional effect can be large, resulting in highly clustered user groups. It can be considered as brand strength from a user-interaction perspective.

Although our model is evaluated only for a couple of datasets, the bidirectional interaction is apparently an essential model for many other online social communities. By identifying communities with high community gravity, future investigations can show how to cultivate strong communities on the Web and how system design and interaction design should be done.

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9. REFERENCES

[1] L. Adamic, J. Zhang, E. Bakshy, and M. Ackerman. Knowledge sharing and yahoo answers: Everyone knows something. In *Proc. WWW2008*, 2008.

[2] E. Adar, L. Zhang, L. Adamic, and R. Lukose. Implicit structure and the dynamics of blogspace. In *Workshop on the Weblogging Ecosystem*, 2004.

[3] A. Anagnostopoulos, R. Kumar, and M. Mahdian. Influence and correlation in social networks. In *Proc. KDD'08*, 2008.

[4] N. Archak, A. Ghose, and P. Ipeirotis. Show me the money! Deriving the pricing power of product features by mining consumer reviews. In *Proc. KDD'07*, 2007.

[5] S. Brown, A. Tilton, and D. Woodside. The case for on-line communities. *The McKinsey Quarterly*, 1, 2002.

[6] C. Forman, A. Ghose, and B. Wiesenfeld. Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research*, 2008.

[7] L. Getoor and C. P. Diehl. Link mining: A survey. *SIGKDD Explorations*, 2(7), 2005.

[8] J. Golbeck. Trust and nuanced profile similarity in online social networks. *Journal of Artificial Intelligence Research*, 2006.

[9] J. Golbeck and B. Parsia. Trust network-based filtering of aggregated claims. *International Journal of Metadata, Semantics and Ontologies*, 2006.

[10] R. Guha, R. Kumar, P. Raghavan, and A. Tomkins. Propagation of trust and distrust. In *Proc. WWW2004*, 2004.

[11] J. Hartline, V. Mirrokni, and M. Sundararajan. Optimal marketing strategies over social networks. In *Proc. WWW2008*, 2008.

[12] D. Kempe, J. Kleinberg, and E. Tardos. Maximizing the spread of influence through a social network. In *Proc. KDD 2003*, 2003.

[13] J. Leskovec, L. Adamic, and B. Huberman. The dynamics of viral marketing. In *Proc. ACM Conference on Electronic Commerce*, 2006.

[14] J. Leskovec, L. Backstrom, R. Kumar, and A. Tomkins. Microscopic evolution of social networks. In *Proc. KDD'08*, 2008.

[15] D. Liben-Nowell and J. Kleinberg. The link prediction problem for social networks. In *Proc. CIKM*, pages 556–559, 2003.

[16] C. Marlow. Investment and attention in the weblog community. In *Proc. HyperText 2006*, 2006.

[17] J. McAlexander, J. Schouten, and F. Koenig. Building brand community. *Journal of Marketing*, 66:38–54, 2002.

[18] M. McPherson, L. Smith-Lovin, and J. Cook. Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, (27):415–444, 2001.

[19] A. Muniz and T. O'Guinn. Brand community. *Journal of Consumer Research*, 27:412–432, 2001.

[20] M. Richardson and P. Domingos. Mining knowledge-sharing sites for viral marketing. In *Proc. SIGKDD'02*, 2002.

[21] P. Singla and M. Richardson. Yes, there is a correlation – from social networks to personal behavior on the web. In *Proc. WWW2008*, 2008.

[22] M. Subramani and B. Rajagopalan. Knowledge sharing and influence in online. social networks via viral marketing. *Communications of the ACM*, pages 300–307, 2003.

[23] V. Vapnik. *The Nature of Statistical Learning Theory*. Springer-Verlag, 1995.

[24] S. Wasserman and K. Faust. *Social network analysis. Methods and Applications*. Cambridge University Press, Cambridge, 1994.

[25] C. Ziegler and J. Golbeck. Investigating correlations of trust and interest similarity. *Decision Support Services*, 2006.