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Experimental Analysis of the Effects of Social Relations on Mobile Application Recommendation

Tomonobu Ozaki and Minoru Etoh

***Abstract*—In this paper, we empirically analyze the effects of social relations on the recommendation of mobile applications in a community of students at a university. We identify three social relations by questionnaires and two relations by students properties, and examine their effects from a wide variety of perspectives in the framework of top-N recommendation by user and item based collaborative filtering with two re-ranking mechanisms. In the analysis, we assess the difference of the effects by the origin and strength of social relations as well as by the methods of collaborative filtering and re-ranking mechanisms. As a result of the analysis, we confirm that appropriate social relations can significantly improve the performance of recommendation, in terms of increasing diversity and novelty with keeping high accuracy, especially for the late adopters.**

***Index Terms*—recommendation, social relation, mobile application**

I. Introduction

RECOMMENDER systems attract a lot of attention as an important information technology to overcome the rapid increase of available information. Accurate and precise recommendations are absolutely necessary for the success of recommender systems.

With the growth of social networks, social relations become to be regarded as promising information sources for improving the accuracy of recommendations [1]–[5]. For instance, the effects of social relations are deeply examined in the domain of movie recommendation [1], while the effects of different kinds of social relations are extensively compared [2], [3]. Furthermore, recommendation methods using social networks based on the collaborative filtering and the matrix factorization are developed in [4] and [5], respectively.

The results of above mentioned researches suggest that the social relations can contribute to recommender systems in terms of improving the accuracy. However, accuracy is not the only measure for the quality of recommender systems. In addition to the accurate recommendations, providing a wide range of valuable and serendipitous information is critically important [6]. Researches on this topic are conducted recently. A method for diversifying recommendation lists is developed [7], while metrics for evaluating the serendipity are proposed [8]–[10]. However, the effects of social relations on recommendations are not extensively analyzed from the other perspectives than accuracy.

In this paper, we prepare five social relations having different origins and different degree of strength, and empirically analyze their effects and significance on the improvement of recommendation of mobile applications from a wide variety of perspectives including accuracy, diversity, novelty and serendipity. We employ a framework of the top-N recommendation based on the collaborative filtering [11] with a re-ranking mechanism. In the framework, social relations are applied (1)to estimate the recommendation strength by collaborative filtering and (2)to prepare the recommendation lists by re-evaluation (re-ranking). The overall flow is shown in Fig. 1.

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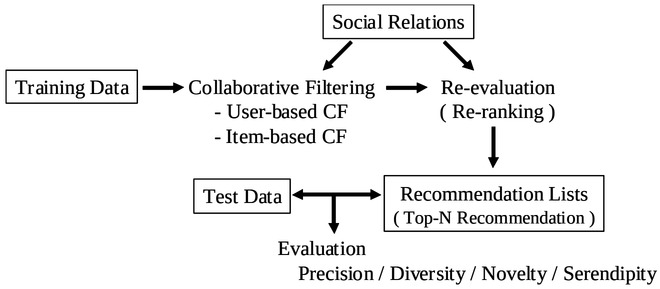

Fig. 1. Overall flow of Recommendation using Social Relations

In the analysis, both of user based collaborative filtering methods [12]–[14] and item based ones [15]–[17] are employed to compare the difference of the effects by recommendation methods. We also compare the differences of the effects by positions where social relations are applied, *i.e.* applications of social relations to (1)collaborative filtering only, (2)re-ranking only and (3)both of collaborative filtering and re-ranking.

The rest of this paper is organized as follows. In section II, we introduce the basic notations, and propose recommendation methods using social relations. Re-evaluation methods are also proposed. In section III, after describing the dataset and evaluation criteria, experimental results are reported. Finally, we conclude the paper and describe future work in section IV.

II. Recommendation with Social Relations

Notations used throughout the paper are summarized in Table I. Let $U = \{u_1, \cdots, u_{|U|}\}$ and $I = \{i_1, \cdots, i_{|I|}\}$ be sets of users and items, respectively. Given a user $x \in U$, a set I_x^+ ($\subseteq I$) denotes a set of items rated by x, while another set $I_x^- = I \setminus I_x^+$ denotes a set of items not rated by x. A positive real number $r_{x,i}$ ($x \in U, i \in I_x^+$) denotes the rating value of x on an item i. Given a user $x \in U$ and an indicator function $R : U \times U \rightarrow \{0, 1\}$ which takes 1 if there exists a social relation R between two users, we denote a set of users having, and not having, the relation R with x as $U_x^+ = \{y \in U : R(x, y) = 1\}$ and $U_x^- = U \setminus (U_x^+ \cup \{x\})$, respectively.

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TABLE I
NOTATIONS

Notation	Description
x, y	users
i, j	items
U	Set of all users
U_x^+	Set of users having a social relation with x
U_x^-	Set of users not having a social relation with x
I	Set of all items
I_x^+	Set of items rated by x
I_x^-	Set of items not rated by x
$r_{x,i}$	Rating value of x on i
$\hat{r}_{x,i}$	Recommendation strength of i for x
$s_{x,y}$	Similarity between x and y
$s_x^{i,j}$	Similarity between i and j of x
$\alpha(\geq 0)$	Weight of users having social relations
$\beta(\geq 0)$	Weight for users not having social relations

In this paper, we consider the top-N recommendation. Therefore, given a user $x \in U$, the first step for obtaining the ranking list of recommendation for x is to estimate the recommendation strength $\hat{r}_{x,i}$ on every item $i \in I_x^-$. In the following subsections, we introduce methods for estimating the recommendation strength based on the user- and item-based collaborative filtering methods by taking into account the social relations, respectively.

A. User-based Collaborative Filtering

User-based collaborative filtering methods [12]–[14] utilize the past ratings of similar users to estimate the recommendation strength. In this paper, we employ a user-based collaborative filtering based on the K-nearest neighbors.

Given two users x and y ($x, y \in U$), we propose a similarity between x and y with consideration of social relations as follows:

$$s_{x,y} = \begin{cases} \alpha \cdot cos(x,y) & (y \in U_x^+) \\ \beta \cdot cos(x,y) & (y \in U_x^-) \end{cases} \tag{1}$$

where $\alpha \geq 0$ and $\beta \geq 0$ are parameters and

$$cos(x,y) = \frac{\sum_{i \in I_x^+ \cap I_y^+} r_{x,i}\, r_{y,i}}{\sqrt{\sum_{i \in I_x^+} r_{x,i}^2}\sqrt{\sum_{i \in I_y^+} r_{y,i}^2}} \tag{2}$$

denotes the cosine similarity based on the past ratings. The strength of social relations in calculating $s_{x,y}$ can be controlled by two parameters α and β. For example, a parameter setting $\alpha = 1$ and $\beta = 0$ utilizes the users having social relations only, while $\alpha = \beta$ ignores the effects of social relations.

The recommendation strength $\hat{r}_{x,i}$ for a user $x \in U$ on an item $i \in I_x^-$ is derived as the weighted sum of ratings on i by the top-K similar users. Let

$$U_{x,K} = \{y \in U_{\neq x} : K > |\{z \in U_{\neq x} : s_{x,y} < s_{x,z}\}|\}$$

be a set of top-K similar users of x where $U_{\neq x} = U \setminus \{x\}$. Then, $\hat{r}_{x,i}$ is formally defined as

$$\hat{r}_{x,i} = \sum_{i \in I_y^+, y \in U_{x,K}} s_{x,y} r_{y,i}. \tag{3}$$

If we set $K = |U| - 1$ for the K-nearest neighbors, then the user-based collaborative filtering can be formalized as a variant of the composite social network approach [18] based on the linear threshold model [19]. In the model, the probability $Pr(x,i)$ that a user x rates an item i is defined as

$$Pr(x,i) = 1 - \exp(-p(x,i))$$

where

$$\begin{aligned} p(x,i) &= \alpha \sum_{y \in U_x^+, i \in I_y^+} cos(x,y) r_{y,i} + \beta \sum_{y \in U_x^-, i \in I_y^+} cos(x,y) r_{y,i} \\ &= \sum_{i \in I_y^+, y \in U_{x,|U-1|}} s_{x,y} r_{y,i} \\ &= \hat{r}_{x,i} \ . \end{aligned}$$

The parameters can be estimated from the past rating behaviors by maximizing the following likelihood function under the constraints of $\alpha \geq 0$ and $\beta \geq 0$:

$$\prod_{x \in U} \left[\prod_{i \in I_x^+} Pr(x,i) \times \prod_{i \in I_x^-} (1 - Pr(x,i)) \right]$$

where the first and second terms correspond to the probabilities that each user does and does not rate the item, respectively.

B. Item-based Collaborative Filtering

Item-based collaborative filtering methods [15]–[17] utilize a similarity among items in general. In this subsection, we propose a personalized similarity among items with the consideration of social relations, and use it for estimating the recommendation strength.

For a set of users $U' \subseteq U$, we define the cosine similarity between two items i and j ($i, j \in I$) by using the past ratings as follows:

$$s(i,j,U') = \frac{\sum_{x \in U', i \in I_x^+, j \in I_x^+} r_{x,i}\, r_{x,j}}{\sqrt{\sum_{x \in U', i \in I_x^+} r_{x,i}^2}\sqrt{\sum_{x \in U', j \in I_x^+} r_{x,j}^2}}. \tag{4}$$

We propose a personalized similarity

$$s_x^{i,j} = \frac{1}{\alpha + \beta}\left(\alpha \cdot s(i,j,U_x^+) + \beta \cdot s(i,j,U_x^-)\right) \tag{5}$$

for a user x between two items i and j. It is the weighted average over cosine similarities for U_x^+ and U_x^- with two parameters $\alpha \geq 0$ and $\beta \geq 0$. As the same as the similarity among users, we can control the strength of social relations in calculating $s_x^{i,j}$.

The recommendation strength is derived based on the rated items. We define the recommendation strength $\hat{r}_{x,i}$ of an item $i \in I_x^-$ for a user x as the summation of similarites between i and a rated item $j \in I_x^+$:

$$\hat{r}_{x,i} = \sum_{j \in I_x} s_x^{i,j}. \tag{6}$$

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C. Re-evaluation of Recommendation Strength by Social Relations

Besides accurate recommendations, the ability of providing a wide variety of new information is one of important factors for recommendation methods [6]–[10]. According to the suggestion in [6], we propose methods for re-evaluating the recommendation strength by using social relations.

For a user $x \in U$ and an item $i \in I_x^-$, the average value of recommendation strength of i over users having social relations with x is defined as

$$\overline{r}_{x,i} = \frac{1}{|U_{(x,i)}|} \sum_{y \in U_{(x,i)}} \hat{r}_{y,i}$$

where $U_{(x,i)} = \{y \in U_x^+ \cup \{x\} : i \in I_y^-\}$.

In order to obtain high degree of diversity and novelty, the updated recommendation strength is obtained by amplifying the original recommendation strength based on the difference from the average:

$$\hat{r}_{x,i} \cdot \frac{\max(\hat{r}_{x,i}, \overline{r}_{x,i})}{\min(\hat{r}_{x,i}, \overline{r}_{x,i})}. \tag{7}$$

The method emphasizes the items having largely different recommendation strength from the average.

We prepare another re-evaluation method having the opposite effects to obtain accurate recommendations:

$$\hat{r}_{x,i} \cdot \frac{\min(\hat{r}_{x,i}, \overline{r}_{x,i})}{\max(\hat{r}_{x,i}, \overline{r}_{x,i})}. \tag{8}$$

This method reduces the recommendation strength largely if it differs greatly from the average. As a result, the recommendation strength of ordinary items in the community increases relatively.

III. Experiments

A. Dataset

To assess the effects of social relations on recommendation tasks, we implement all methods in Java and conduct experiments. We use a log data of mobile application executions collected from February to July 2011 with 157 students in Osaka University. The dataset is divided into two disjoint sets according to the timestamps. The dataset for the first three months is used to make the recommendation. After removing the log of mobile applications used by less than three students, a training data containing 377 applications with 8,576 ratings is obtained. We use the value of $\ln(1 + \#$ of days when x uses i during the first three months) as $r_{x,i}$. On the other hand, we prepare two test data from the dataset of last three months. As the top 10% of late adopters, we select 15 active students who install at least 10 applications in the training data during the last three months. We denote the set of active students as U^{10}. Similarly, the second test set U^5 consists of 58 students who install at least 5 applications. For the training and test data, a relation $U \supset U^5 \supset U^{10}$ holds.

We identify the following three social relations by questionnaires:

1) R_T: friendly enough to talk with each other,
2) R_M: friendly enough to send and receive emails, and
3) R_C: friendly enough to make telephone calls.

TABLE II
Average number of users having social relations

	R_T	R_M	R_C	R_2	R_3
U (157 students)	17.4	9.6	6.1	52.8	22.6
U^5(58 students)	16.1	9.5	6.1	52.4	24.7
U^{10}(15 students)	13.5	8.5	5.1	57.3	25.9

In addition, based on three user properties (1)gender (male or female), (2)major (art or science), and (3)location of campus (one of three places), we prepare two quasi-relations roughly capturing the homophily [20]:

1) R_2: at least two properties are the same, and
2) R_3: all properties are the same.

We believe that the inequalities $R_T < R_M < R_C$ and $R_2 < R_3$ hold on the strength of social relations. The average numbers of users having social relations are summarized in Table II.

B. Evaluation Criteria

Given a set of test users $U^t \subseteq U$, the macro average

$$V_*(U^t) = \frac{1}{|U^t|} \sum_{x \in U^t} v_*(x, N)$$

of a measure $v_*(x, N)$ defined below over U^t is employed as an evaluation criterion. Four evaluation measures are prepared. In the following definitions, we denote the top-N recommendation items for a user $x \in U$ as

$$P(x, N) = \{i \in I_x^- \ : \ N > |\{j \in I_x^- \ : \ \hat{r}_{x,i} < \hat{r}_{x,j}\}|\},$$

while the answer set for x is denoted as $A(x)$ ($\subseteq I_x^-$).

1) $v_p(x, N)$: The first measure is weighted precision@N, formally defined as

$$v_p(x, N) = \frac{\sum_{i \in A(x) \cap P(x,N)} r'_{x,i}}{\sum_{i \in P(x,N)} r'_{x,i}} \tag{9}$$

where

$$r'_{x,i} = \begin{cases} r_{x,i} & (i \in A(x)) \\ \sum_{j \in A(x)} r_{x,j} \,/\, |A(x)| & (i \notin A(x)) \end{cases}.$$

We use the rating value, *i.e.* $\ln(1 + \#$ of days when x uses i during the last three months), as the weight. The average value is used for the items having no rating.

2) $v_d(x, N)$: As the second measure, we employ the diversity, *i.e.* the average of cosine distance among items in $P(x, N)$:

$$v_d(x, N) = \frac{\sum_{i \in P(x,N)} \sum_{j \in P(x,N), i \neq j} (1 - s(i, j, U))}{|P(x, N)| \, (|P(x, N)| - 1)}. \tag{10}$$

3) $v_n(x, N)$: The third measure is the novelty which is defined as the average of minimum distance between rated items and predicted ones:

$$v_n(x, N) = \frac{1}{|P(x, N)|} \sum_{i \in P(x,N)} \min_{j \in I_x^+} (1 - s(i, j, U)). \tag{11}$$

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TABLE III
RESULTS OF THE BASELINE METHODS

	U^5			U^{10}		
	V_p	V_d	V_n	V_p	V_d	V_n
U(156)	0.289	0.228	0.264	0.393	0.210	0.241
U(15)	0.284	0.236	0.268	0.368	0.213	0.239
I()	0.281	0.198	0.230	0.352	0.179	0.209

4) $v_s(x, N)$: The last measure is the serendipity. It is the ratio of correctly recommended items which are not recommended by a baseline method:

$$v_s(x, N) = \frac{|P(x, N) \cap A(x) \setminus P'(x, N)|}{|P(x, N)|} \tag{12}$$

where $P'(x, N)$ denotes the top-N recommendation by the baseline method, *i.e.* the recommendation without social relations ($\alpha = \beta = 1$) and the re-evaluation.

In addition to the macro average $V_*(U^t)$, we employ the gain ratio of macro average from a baseline method as additional evaluation criteria:

$$G_*(U^t) = V_*(U^t)/V'_*(U^t)$$

where $V'_*(U^t)$ denotes the macro average of the baseline method. Furthermore, to evaluate the balanced gain, we employ the harmonic mean of gains on accuracy and other measure:

$$H_*(U^t) = 2/(1/G_p(U^t) + 1/G_*(U^t)).$$

C. Results

We set $N = 10$ for the top-N recommendations throughout the experiments. The parameters (α, β) is set to (1.2, 1.0), (1.5, 1.0), (3.0, 1.0), (1.0, 0.0) or (opt, opt) where "opt" denotes the value obtained by the maximum likelihood estimation in section II, while K in the user-based collaborative filtering is set to 15 or 156 (=$|U| - 1$). For each test data, we obtain 258 results including the baselines by the combination of above parameters and estimation methods for recommendation strength with and without social relations.

1) Results of the baseline methods: We show the results of baseline methods in Table III. From the results, the user-based collaborative filtering with $K = 156$, denoted as "U(156)", achieves the best performance, while the item-based method, denoted as "I()", gets the worst among the baseline methods. Regardless of the methods, the results of U^{10} is better than those of U^5 on the precision. The opposite relations are observed on the diversity and novelty. In other words, we obtain accurate but non-diversified recommendation lists for late adopters.

2) Best results of recommendation by social relations: We summarize the best three results with respect to each evaluation criterion in Table IV. In the table, each entry is in the form of

"value: method, (α, β), re-eval, social relation"

where 're-eval' is one of 'amp': re-evaluation of formula (7) is applied, 'red': re-evaluation of formula (8) is applied, or '–': re-evaluation is not applied. Note that, (α, β)=(1.0,1.0) means that we apply re-evaluation to the original recommendation strength derived by ignoring social relations.

The best results using social relations outperform the baseline methods in all evaluation criteria. As similar to the baseline methods, user-based collaborative filtering achieves the accurate recommendations. U(156) and U(15) with re-evaluation method 'amp' take the first place on V_p in U^5 and U^{10}, respectively. It is surprising that 'amp' contributes to gaining the accuracy since it is prepared for the purpose of diversified recommendations. The method 'amp' with parameter 'opt' and social relation R_C performs the best

TABLE IV
BEST-3 RESULTS W.R.T. EACH EVALUATION CRITERION

U^5	U^{10}
V_p	
0.303: U(156), (3.0,1.0), amp, R_T	0.419: U(15), (1.2,1.0), amp, R_3
0.302: U(156), (opt,opt), –, R_C	0.413: U(156), (1.0,1.0), amp, R_3
0.301: U(156), (3.0,1.0), –, R_T	0.413: U(156), (1.2,1.0), amp, R_3
V_d	
0.329: I(), (opt,opt), amp, R_C	0.289: I(), (opt,opt), amp, R_C
0.306: U(156), (1.0,0.0), red, R_C	0.277: I(), (opt,opt), amp, R_M
0.306: I(), (opt,opt), amp, R_M	0.275: I(), (1.0,0.0), amp, R_C
V_n	
0.437: I(), (opt,opt), amp, R_C	0.359: I(), (opt,opt), amp, R_C
0.391: I(), (opt,opt), amp, R_M	0.340: I(), (opt,opt), amp, R_M
0.389: I(), (3.0,1.0), amp, R_C	0.336: I(), (1.0,0.0), amp, R_C
V_s	
0.081: I(), (1.0,0.0), amp, R_C	0.167: I(), (1.5,1.0), amp, R_T
0.071: I(), (1.5,1.0), amp, R_C	0.167: I(), (1.2,1.0), amp, R_T
0.071: I(), (1.2,1.0), amp, R_C	0.154: I(), (1.0,0.0), amp, R_T
V_s under the condifion of $G_p \geq 1.0$	
0.059: U(15), (1.2,1.0), red, R_2	0.130: I(), (1.0,0.0), –, R_T
0.053: U(15), (1.2,1.0), red, R_T	0.120:,I(), (3.0,1.0), –, R_T
0.047: U(15), (1.2,1.0), –, R_T	0.120: I(), (opt,opt), –, R_M
G_p	
1.048: U(15), (1.2,1.0), red, R_2	1.139: U(15), (1.2,1.0), amp, R_3
1.047: U(156), (3.0,1.0), amp, R_T	1.125: I(), (opt,opt), red, R_T
1.043: U(15), (1.0,1.0), red, R_3	1.116: I(), (1.5,1.0), –, R_T
G_d	
1.659: I(), (opt,opt), amp, R_C	1.615: I(), (opt,opt), amp, R_C
1.544: I(), (opt,opt), amp, R_M	1.549: I(), (opt,opt), amp, R_M
1.541: I(), (3.0,1.0), amp, R_C	1.533: I(), (1.0,0.0), amp, R_C
G_d under the condifion of $G_p \geq 1.0$	
1.090: U(15), (1.0,1.0), amp, R_T	1.264: I(), (1.0,0.0), red, R_T
1.084: U(15), (1.0,1.0), amp, R_M	1.241: I(), (1.0,0.0), –, R_T
1.069: U(15), (1.2,1.0), –, R_T	1.191: U(15), (opt,opt), amp, R_3
G_n	
1.900: I(), (opt,opt), amp, R_C	1.719: I(), (opt,opt), amp, R_C
1.701: I(), (opt,opt), amp, R_M	1.632: I(), (opt,opt), amp, R_M
1.690: I(), (3.0,1.0), amp, R_C	1.611: I(), (1.0,0.0), amp, R_C
G_n under the condifion of $G_p \geq 1.0$	
1.090: U(15), (1.0,1.0), amp, R_T	1.298: I(), (1.0,0.0), red, R_T
1.089: U(15), (1.0,1.0), amp, R_M	1.279: I(), (1.0,0.0), –, R_T
1.073: I(), (1.2,1.0), –, R_M	1.234: U(15), (opt,opt), amp, R_3
H_d	
1.062: U(15), (3.0,1.0), red, R_C	1.160: I(), (1.0,0.0), red, R_T
1.058: I(), (1.0,0.0), red, R_T	1.141: U(15), (1.2,1.0), amp, R_3
1.058: U(15), (1.2,1.0), amp, R_T	1.132: U(15), (1.0,1.0), amp, R_2
H_d under the condifion of $G_p \geq 1.0$	
1.052: U(15), (1.0,1.0), amp, R_M	1.160: I(), (1.0,0.0), red, R_T
1.051: U(15), (1.0,1.0), amp, R_T	1.141: U(15), (1.2,1.0), amp, R_3
1.046: U(15), (1.0,1.0), amp, R_C	1.132: U(15), (1.0,1.0), amp, R_2
H_n	
1.070: U(15), (3.0,1.0), red, R_C	1.174: I(), (1.0,0.0), red, R_T
1.063: U(15), (1.2,1.0), amp, R_T	1.160: U(15), (1.2,1.0), amp, R_3
1.063: I(), (1.0,0.0), red, R_T	1.139: I(), (1.0,0.0), –, R_T
H_n under the condifion of $G_p \geq 1.0$	
1.054: U(15), (1.0,1.0), amp, R_M	1.174: I(), (1.0,0.0), red, R_T
1.051: U(15), (1.0,1.0), amp, R_T	1.160: U(15), (1.2,1.0), amp, R_3
1.046: U(15), (1.2,1.0), red, R_T	1.139: I(), (1.0,0.0), –, R_T

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on V_d and V_n. It also derives a significant performance on G_d and G_n.

Social relations realize the diversified recommendations in I(). While I() is the worst in the baseline method regardless of evaluation criteria, I() with social relations gets the best results on V_d and V_n. In addition, I() with social relation is the most serendipitous. The best value of V_s in U^{10} is almost double of that in U^5. From the results, even if we consider the difference between accuracies in U^5 and U^{10}, we can confirm that social relations give larger effects on the serendipity for the late adopters.

We obtain at most 5% and 14% of performance gains on accuracy in U^5 and U^{10}, respectively. In addition, about 10% of performance gain on diversity and novelty under the constraint on accuracy are obtained in U^5, while about 20% of gains are observed in U^{10}. These gains indicate that appropriate social relations succeed in preparing the recommendation lists having wide variety of items without decreasing accuracy. The success can be confirmed from the results of H_d and H_n. We obtain 5% and 15% of average gains in U^5 and U^{10}, respectively. The gains in U^{10} are much larger than those in U^5. Thus, we can conclude that, similar to the serendipity, social relations improve the performance of recommendation greatly for the late adopters.

3) Comparisons among different methods and social relations: In Table V, we show the average values of each evaluation criterion from three different aspects, (1)methods of collaborative filtering, (2)combinations with re-evaluations and (3)social relations. In the table, while 'w.o. re' means the recommendation using social relation without re-evaluation, 'amp' and 'red' denote the naive or baseline methods with re-evaluation based on formula (7) and (8), respectively. The recommendations using social relations with re-evaluations are denoted as 'w. amp' and 'w. red'.

The results in U^5 and U^{10} have similar tendency especially on the gain ratios and harmonic means. U(15) has the best values on H_d and H_n. In addition, compared with other methods, the value of V_s in U(15) is not small. Thus, it seems to be the best among three methods of collaborative filtering. U(156) receives little effect from social relations since the gain ratios are near from the value of 1.0. On the other hand, smaller loss of accuracy and larger gains of diversity and novelty in I() indicate that social relations give a significant impact to I().

While social relations can not improve the accuracy on average, the re-evaluation method 'red' with baseline methods achieves the best performs on accuracy. On the other hand, the method 'amp' increases diversity and novelty. These results show that re-evaluation methods work as expected. We prepare 'amp' for the diversified recommendations and 'red' for the accurate ones.

Compared with 'amp', the gains on diversity and novelty increase in 'w. amp', but the gain on accuracy decreases. The same relation is observed between 'red' and 'w. red'. The combination of the re-evaluation methods and the collaborative filtering using social relations does not produce the better results on average. In fact, the method 'amp' with baseline methods takes the first place from the aspect of balanced performance gains, *i.e.* H_d and H_n. The second best seems to be 'o.w. re', the recommendation without re-evaluation. Note that the above discussion is valid for the average. As shown in Table IV, the appropriate combinations significantly improve the quality of recommendation.

While a social relation R_C contributes to improving the diversity and novelty, R_T is good for improving the accuracy. It performs the best from the aspect of balanced performance gains. The quasi-relations R_2 and R_3 have similar values of harmonic means with R_M and R_C. But, they have different characteristics. Confirmed by G_d and G_n, social relations identified by questionnaires give large effects to the recommendation. On the contrary, the effects of R_2 and R_3 seem to be small. Besides their origin, we guess that the difference of characteristics partially comes from the difference of the sizes of social relations. R_2 and R_3 have a large number of users on average.

Table VI shows the percentages of improved cases, *i.e.* recommendations having the value greater than 1.0. In the table, H_d^v (H_n^v) denotes H_d (H_n) under the condition of $G_d, G_p \geq v$ ($G_n, G_p \geq v$).

The overall tendency of the results is similar to the previous one in Table V. U(15) shows better performance among the methods of collaborative filtering. Re-evaluation method 'red' greatly improves the accuracy compared with other methods. R_T achieves balanced improvements with high probabilities.

The performance improvements on diversity and novelty are observed in more than 80% of cases in U^5 and 75% in U^{10}. In addition, we achieve the balanced improvements on $H_d^{0.95}$ and $H_n^{0.95}$ in more than 50% of cases in U^{10}. More than 30% of cases are improved on $H_d^{1.0}$ and $H_n^{1.0}$. From the results, we can confirm that social relations have positive effects for improving a wide variety of qualities on recommendation simultaneously.

IV. Conclusion

In this paper, we empirically analyze the effects of social relations on the top-N recommendation of mobile applications by the collaborative filtering approaches from a wide variety of perspectives. The experimental results show that appropriate social relation can gain the performance of recommendation especially for late adopters.

For future work, we plan to investigate a deep examination of the reciprocal effects among multiple social relations on the recommendation. In addition, we believe that a comprehensive analysis of the effects in more sophisticated recommendation techniques such as probabilistic model [21], [22] and matrix factorization [5], [23] is one of promising research directions. Using knowledge obtained in the analysis, we plan to develop a method of selecting appropriate social relations for each user in order to realize an accurate personalized recommendation with high ability of providing diversified and valuable information.

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TABLE V
AVERAGE VALUES OF EACH EVALUATION CRITERION

	U^5									U^{10}								
	V_p	V_d	V_n	V_s	G_p	G_d	G_n	H_d	H_n	V_p	V_d	V_n	V_s	G_p	G_d	G_n	H_d	H_n
U(156)	0.28	0.24	0.28	0.01	0.98	1.04	1.04	1.00	1.00	0.38	0.22	0.25	0.02	0.97	1.03	1.03	0.99	0.99
U(15)	0.27	0.26	0.30	0.04	0.94	1.11	1.13	1.01	1.02	0.36	0.24	0.27	0.07	0.99	1.11	1.12	1.04	1.04
I()	0.25	0.23	0.27	0.04	0.90	1.14	1.16	0.99	1.00	0.33	0.21	0.25	0.08	0.93	1.16	1.18	1.02	1.02
w.o. re	0.27	0.24	0.28	0.03	0.96	1.08	1.09	1.01	1.02	0.37	0.22	0.25	0.05	0.99	1.08	1.09	1.03	1.03
amp	0.28	0.23	0.27	0.02	0.99	1.05	1.05	1.02	1.02	0.37	0.22	0.25	0.05	0.99	1.09	1.09	1.04	1.04
red	0.29	0.22	0.25	0.02	1.00	0.99	1.00	1.00	1.00	0.38	0.20	0.23	0.04	1.04	0.99	1.00	1.01	1.02
w. amp	0.25	0.25	0.30	0.04	0.89	1.16	1.19	0.99	0.99	0.34	0.23	0.27	0.07	0.90	1.17	1.19	1.00	1.01
w. red	0.27	0.24	0.28	0.03	0.95	1.07	1.09	1.00	1.01	0.36	0.21	0.25	0.05	0.98	1.07	1.08	1.02	1.02
R_T	0.27	0.24	0.28	0.04	0.96	1.11	1.12	1.02	1.02	0.37	0.22	0.26	0.07	0.99	1.12	1.13	1.05	1.05
R_M	0.26	0.25	0.29	0.03	0.92	1.13	1.15	1.00	1.01	0.35	0.23	0.26	0.06	0.94	1.13	1.14	1.01	1.02
R_C	0.26	0.25	0.30	0.04	0.91	1.16	1.19	1.00	1.00	0.34	0.23	0.27	0.06	0.92	1.15	1.17	1.00	1.01
R_2	0.27	0.23	0.26	0.02	0.96	1.03	1.04	0.99	1.00	0.36	0.21	0.24	0.04	0.98	1.03	1.05	1.00	1.01
R_3	0.27	0.23	0.27	0.03	0.95	1.05	1.06	1.00	1.00	0.36	0.21	0.25	0.05	0.98	1.06	1.08	1.01	1.02
all	0.27	0.24	0.28	0.03	0.94	1.10	1.11	1.00	1.01	0.36	0.22	0.25	0.06	0.96	1.10	1.11	1.01	1.02

TABLE VI
PERCENTAGES OF IMPROVED RECOMMENDATIONS

	U^5									U^{10}								
	G_p	G_d	G_n	H_d	$H_d^{0.95}$	$H_d^{1.0}$	H_n	$H_n^{0.95}$	$H_n^{1.0}$	G_p	G_d	G_n	H_d	$H_d^{0.95}$	$H_d^{1.0}$	H_n	$H_n^{0.95}$	$H_n^{1.0}$
U(156)	0.49	0.75	0.65	0.59	0.55	0.29	0.62	0.56	0.19	0.51	0.40	0.61	0.49	0.45	0.19	0.54	0.49	0.25
U(15)	0.15	0.87	0.87	0.68	0.38	0.11	0.78	0.46	0.11	0.54	0.87	0.89	0.84	0.67	0.41	0.86	0.69	0.44
I()	0.07	1.00	1.00	0.48	0.29	0.07	0.53	0.29	0.07	0.38	0.96	1.00	0.68	0.58	0.34	0.72	0.58	0.38
w.o. re	0.25	0.88	0.83	0.69	0.51	0.17	0.73	0.52	0.12	0.53	0.75	0.85	0.77	0.68	0.36	0.81	0.69	0.40
amp	0.47	0.87	0.87	0.80	0.67	0.33	0.80	0.67	0.33	0.60	0.93	0.93	0.60	0.53	0.53	0.80	0.67	0.53
red	0.53	0.67	0.60	0.40	0.40	0.33	0.53	0.53	0.33	0.73	0.40	0.53	0.53	0.53	0.40	0.60	0.60	0.40
w. amp	0.20	0.91	0.91	0.51	0.31	0.11	0.57	0.32	0.11	0.37	0.88	0.96	0.64	0.49	0.27	0.65	0.49	0.33
w. red	0.16	0.88	0.83	0.55	0.36	0.12	0.61	0.41	0.05	0.44	0.64	0.73	0.64	0.53	0.25	0.65	0.56	0.28
R_T	0.39	0.90	0.80	0.88	0.57	0.29	0.92	0.57	0.20	0.59	0.75	0.78	0.92	0.69	0.37	0.94	0.71	0.41
R_M	0.31	0.84	0.78	0.71	0.53	0.18	0.75	0.53	0.12	0.53	0.80	0.80	0.65	0.55	0.35	0.69	0.57	0.35
R_C	0.27	0.86	0.84	0.69	0.43	0.16	0.71	0.43	0.14	0.37	0.84	0.84	0.63	0.45	0.27	0.69	0.49	0.27
R_2	0.10	0.82	0.82	0.29	0.27	0.06	0.29	0.27	0.06	0.47	0.57	0.80	0.53	0.51	0.22	0.59	0.55	0.33
R_3	0.12	0.94	0.94	0.35	0.24	0.10	0.55	0.39	0.10	0.41	0.76	0.94	0.63	0.63	0.35	0.63	0.63	0.39
all	0.24	0.87	0.84	0.58	0.41	0.16	0.64	0.44	0.12	0.47	0.75	0.84	0.67	0.56	0.31	0.71	0.59	0.35

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