Implicit Influencing Group Discovery from Mobile Applications Usage*

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SUMMARY This paper presents an algorithmic approach to acquiring the influencing relationships among users by discovering implicit influencing group structure from smartphone usage. The method assumes that a time series of users’ application downloads and activations can be represented by individual inter-personal influence factors. To achieve better predictive performance and also to avoid over-fitting, a latent feature model is employed. The method tries to extract the latent structures by monitoring cross validating predictive performances on approximated influence matrices with reduced ranks, which are generated based on an initial influence matrix obtained from a training set. The method adopts Nonnegative Matrix Factorization (NMF) to reduce the influence matrix dimension and thus to extract the latent features. To validate and demonstrate its ability, about 160 university students voluntarily participated in a mobile application usage monitoring experiment. An empirical study on real collected data reveals that the influencing structure consisted of six influencing groups with two types of mutual influence, i.e. intra-group influence and inter-group influence. The results also highlight the importance of sparseness control on NMF for discovering latent influencing groups. The obtained influencing structure provides better predictive performance than state-of-the-art collaborative filtering methods as well as conventional methods such as user-based collaborative filtering techniques and simple popularity.

key words: influence, latent structure, user behavior modeling, mobile application, android, viral marketing

1. Introduction

A recent study shows that asymmetric inter-personal influence may play an important role in understanding user adoption patterns and creating item recommendations with significantly better performance [2]. Given that user $B$ tends to purchase products that user $A$ has already bought, we should extract the implicit influencing relationship $A \rightarrow B$. Implicit influence includes indirect influence (influence through mediators with no direct interaction between $A$ and $B$) as discussed in Liu’s work [3] and also tendency effects such as user $A$ simply tending to purchase at an earlier stage since he/she prefers innovative products, as well as direct influence through interaction with surrounding friends like $A$ and $B$. This paper shows how to obtain inter-personal implicit influence factors by observing only purchase histories.

Related works on influence factors include several models that simulate information diffusion through a network. Widely-used models include the independent cascade (IC) model and the linear threshold (LT) model; both are fundamental probabilistic models of information diffusion [4], [5]. The IC model assumes that the social network structure is given and requires diffusion probabilities associated with links to be specified as input parameters. The LT model also assumes that the social network structure is given. In the LT model, each edge is assigned a weight. When the sum of weights exceeds a probabilistic threshold, diffusion occurs on edges from surrounding nodes that have been activated by information. Based on these models, several methods have been proposed; they estimate diffusion probabilities as a maximization problem [6]–[9]. Besides the IC/LT model, Song proposed the prediction of future adoption by the information flow network [10], which can be created from adoption history. Kawamae proposed personal innovator degree [2], which assumes that influence decreases exponentially as time passes, to predict future adoption. All of those published influence-related methods need to estimate each inter-personal influence factor independently. The number of factors to be estimated equals the number of edges of the given social network, since diffusion is assumed to occur only through edges of the social graph. The IC/LT models that simulate information diffusion occur on edges from surrounding nodes that have been activated by information. Based on these models, several methods have been proposed; they estimate diffusion probabilities as a maximization problem [6]–[9]. Besides the IC/LT model, Song proposed the prediction of future adoption by the information flow network [10], which can be created from adoption history. Kawamae proposed personal innovator degree [2], which assumes that influence decreases exponentially as time passes, to predict future adoption. All of those published influence-related methods need to estimate each inter-personal influence factor independently. The number of factors to be estimated equals the number of edges of the given social network, since diffusion is assumed to occur only through edges of the social graph. For implicit influencing relationships, however, the diffusion network cannot be obtained beforehand, since it includes indirect influences and tendency effects. Thus, we cannot apply those methods if the number of users is high, due to the high computational complexity required to estimate each influence factor independently for every pair of users. Moreover, there exists another difficulty with the influence modeling approach. Since only common items adopted by both users can be used to acquire influence factors, the number of adopted items available for calculation tends to be small. This causes rough and unstable estimation for each influence probability.

In order to cope these difficulties, the authors propose to apply the latent feature model through matrix factorization. The recent success of collaborative filtering based on matrix factorization motivated the authors into applying the technique for influence modeling. Considering influence factors as probabilities on the context of information diffusion, the factor should be non-negative. Thus the authors employ NMF (non-negative matrix factorization) [11], [12] as a promising matrix factorization method.

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NMF has emerged as a powerful tool since it offers data analysis with enhanced interpretability. It was originally proposed as a method for identifying matrix factors with part-of-whole interpretations [11]. NMF was later successfully applied to feature extraction in various fields such as music analysis, text mining, and gene analysis as well as image processing, see Weixiang’s survey [12]. Moreover, a recent study proposed a community discovery method based on NMF [13].

We validate the model through an extensive empirical study at Osaka University involving 160 students. The study reveals several important findings as follows;

- Sparseness control by regularization is important — sparse feature vectors achieve better predictive performance
- Sparse feature vectors imply latent group structure in influencing relationship

Figure 1 shows the influencing structure acquired from the actual smartphone usage data. Each node and its color represents a user and his/her influencing group (G1 through G6). Each edge represents a major influencing relationship whose strength exceeds a threshold. Here, influencing groups are determined by latent features on influencing pattern rather than connectivity and/or density of edges. Therefore, it is different from community discovery on influencing relationship. Since intra-group influences tend to be strong compared with inter-group influences, the figure looks like a result of community discovery. However, it should be noted that the basic meaning is totally different. Further details of Fig. 1 are described in Sect. 3.3.

The authors have selected application usage of smartphones as the target of this implicit influence analysis. The reason is the increasing importance of understanding users’ behavior on smartphones, since they are being rapidly adopted and appear likely to replace traditional cellular phones globally. The method described in this paper can be applied to any adoption history, not just application usage of smartphones.

To the best of our knowledge, this is the first paper to describe an attempt to apply the latent feature model to handling user influence relationships with validation by actual user data. Noteworthy contributions of this paper are as follows;

- Proposing a latent feature model on inter-personal implicit influence relationships that offers better predictive performance
- An extensive empirical study on real smartphone usage data involving 160 Osaka University students over a 4 month period; the results reveal latent group structure, confirm the importance of sparseness control over influence matrices, and demonstrate the proposals superiority over existing state-of-the-art methods

The authors verify its validity and effectiveness through an empirical study on actual, but specific, data. Although it is obvious that the model’s validity and effectiveness depends on data, i.e. user behaviors, the authors believe this work does provide insights on a model that is worthy of being tested for similar setting tasks.

The structure of the rest of the paper is as follows. Section 2 overviews the problem and the model formulation. Section 3 explains the data collected and the experiments conducted. The experiments include latent group discovery and predictive performance evaluation. Section 4 provides additional discussions. Section 5 concludes the paper.

2. Inter-Personal Influence

2.1 Asymmetric Relationship

Figure 2 shows a simple example of the application adoption logs of 3 users (user 1, 2, 3) with 5 applications. Here, the horizontal axis represents time. A circle with number represents that the user adopted the corresponding application at that time. It is obvious the user-application relationships yields cascades, sequences of users who adopted an application (blue solid arrows). The goal is to predict future application adoption on each user for personalized recommendations. In the typical collaborative filtering (CF) approach, the next adoption by user 1 is predicted from the data of user 2 and user 3 since they have same degree of similarity as user 1 and, of key importance, CF does not take the order into account. Thus, applications 4 and 5 will be recommended equally by CFs. However, if we attend to the order of adoption, it is obvious that user 2 precedes user 1, while user 3 follows user 1. Thus user 1 is more likely to adopt application 5 than application 4. This clearly illustrates the importance of incorporating inter-personal influence when
making predictions.

2.2 Overview of Discovering Influencing Groups

Figure 3 overview the influencing group discovery process targeted by this paper. Based on a training set, initial influence matrix $R$ is calculated. Next, $R$ is fed to matrix factorization (NMF) to generate approximated influence matrices $\tilde{R}$ with reduced ranks. The Application Adoption Predictor predicts future application adoption for each user using $\tilde{R}$ and the training set. Predictive performance is calculated by comparing predictive results with the test set data in the cross-validation manner. The following sections will detail each component.

2.3 Influence Factors from Observations

In this section, the authors define the influence factors for $R$, which is similar to the static model described in Goyal’s work [9]. The key difference is that we do not assume the existence of a given social network, since we cannot observe it in reality. Therefore, we need to predict influence factors for all users from observed application usage data.

2.3.1 Frequency-Based Influence Modeling

Under this model, user $u$ has static influence probability $P_r(u \rightarrow v)$ for user $v$. After user $u$ invokes application $d$, he/she tries to influence his/her inactive (yet to invoke $d$) neighbor $v$ anytime within a certain time period $\tau$. Here, parameter $\tau$ is assumed to be constant. Each attempt is viewed as a Bernoulli trial, so the Maximum Likelihood Estimator of successful probability is the ratio of number of successful attempts over the total number of trials. Hence, the influence probability of $u$ on $v$ is estimated as:

$$ P_r(u \rightarrow v) = \frac{\|A_{u\rightarrow v}\|}{\|A_u\|} , \quad (1) $$

where $\|A_u\|$ denotes the number of applications which user $u$ invokes in the training set. $\|A_{u\rightarrow v}\|$ denotes the number of applications which user $u$ invoked then $v$ invoked in the training set.

Let $P_{inf}(d|u)$ be a joint influence probability for application $d$ on user $u$ from surrounding neighbors. In this paper, we assume that the probability of various friends influencing $u$ is independent of each other. Hence, the joint probability $P_{inf}(d|u)$ can be defined as follows:

$$ P_{inf}(d|u) = \left[ 1 - \prod_{v} \left( 1 - P_r(u' \rightarrow u) Y(u',d) \right) \right] , \quad (2) $$

$$ Y(u',d) = \begin{cases} 1 & \text{if user } u' \text{ has invoked application } d \\ 0 & \text{otherwise} \end{cases} . \quad (3) $$

2.3.2 Influence Modeling Improvement by Entropy

There is a wide variety of applications, i.e., from very popular items to niche items. The latter have inherently higher possibilities of spreading through personal influence. Taking this into account, the authors propose an entropy-based influence factor. Entropy can be considered as an indicator of rarity. In the modeling proposal, we obtain the application entropy from the number of its unique users. Hence, the proposed entropy-based influence probability $\hat{P}_r(u \rightarrow v)$ is defined as follows:

$$ \hat{P}_r(u \rightarrow v) = \frac{\sum_{a \in A_u} \left( -\log \left( \frac{u_a}{U_{glob}} \right) \right) }{\sum_{a \in A_u} \left( -\log \left( \frac{u_a}{U_{glob}} \right) \right) } , \quad (4) $$

where $U_{glob}$ denotes the total possible number of users for applications (Android applications in the experiment) and $u_a$ denotes the number of unique users of application $a$. It is difficult to know the true values of $u_a$ and $U_{glob}$. As a substitute for the true value of $u_a$, the authors apply the approximate number of downloads recorded by “Android Market”. For $U_{glob}$, the tentative value of 2,000,000 was applied in the experiment. In order to obtain $P_{inf}(d|u)$ on $\hat{P}_r(u' \rightarrow u)$, Eq. (2) has no need to be modified if $\hat{P}_r(u' \rightarrow u)$ is applied instead of $P_r(u' \rightarrow u)$.

The authors performed pre-evaluation experiments that compared frequency-based modeling and entropy-based modeling. The results showed that the latter has better performance with slight margins. Therefore, entropy-based modeling is used in the later part of this paper. The effects of parameter $\tau$ were also been pre-evaluated. The results showed that longer is the better under the limited conditions examined. Therefore, all experiments in this paper were carried out under the condition of $\tau = \infty$.

Let user influence matrix $R$ be a $U_{exp} \times U_{exp}$ matrix which has value of $P_r(u \rightarrow v)$ as an element for row $u$ and column $v$, where $U_{exp}$ denotes the number of subjects participating in the experiment.

2.4 Latent Feature Model

Recently proposed state-of-the-art CFs employ the latent
feature model based on matrix factorization [14]. In case of CF, the user–item matrix is factorized, so that it acquires latent user feature and latent item feature. Here, the authors propose to factorize the user influence matrix $R$ (user–user matrix) by NMF.

NMF decomposes one non-negative matrix $X$ ($n \times m$ matrix) into two non-negative matrices $A$ ($n \times k$ matrix) and $B$ ($k \times m$ matrix) with reduced dimension $k$ ($k \ll n, m$) as a result of factorization, such that $X \approx AB$. Here, let us call matrix $AB$ ($n \times m$ matrix) the approximated matrix of $X$ with reduced rank $k$; we depict it as $\hat{X}^{(k)}$. NMF has the unique feature of keeping values non-negative through decomposition as a constraint.

Subjecting user influence matrix $R$ to NMF yields approximated matrix $\hat{R}^{(k)}$ with reduced rank $k$. Since $R$ and $\hat{R}^{(k)}$ are matrices of the same size, the method to predict users’ application adoptions by the influence matrix $R$ can be applied to $\hat{R}^{(k)}$ without any change.

To find optimal operational boundary in terms of prediction performance, we tested several NMF variations with parameter search; NMF requires an inherently non-linear optimization process and so outputs different decomposition results. Table 1 shows the list of NMF algorithms used for the experiments. All NMF computations were performed using the package NMF [15] in R [16]. By observing the optimal operational boundary in prediction performance by approximated influence matrices $\hat{R}^{(k)}$ while sweeping rank $k$, we are able to find the most likely number of the latent feature dimension of the inter-personal relationship.

### Table 1 NMF algorithms.

| #  | Ref. | Description                                                                 |
|----|------|------------------------------------------------------------------------------|
| 1  | [17] | Standard NMF, based on Kullbach-Leibler divergence                           |
| 2  | [18] | Standard NMF, based on Euclidean distance                                    |
| 3  | [19] | Non-smooth NMF based on Kullbach-Leibler divergence                          |
| 4  | [20] | Modified version of [18] based on Euclidean distance                        |
| 5  | [21] | Pattern-Expression NMF based on Euclidean distance                           |
| 6  | [22] | Alternating Least Square (ALS) approach                                      |

3. Data and Experiments

3.1 Collected Data

The authors have been monitoring the usage of smartphones in collaboration with Osaka University. 160 university students voluntarily participated in the monitoring process. Possible participants were requested to apply in a group of less than 50 students. Consequently 160 students consisted of six communities (groups of friends). Experimental usage monitoring software was installed on each of the smartphones, Xperia®, provided to the students with informed consent on data collection and its use for research purposes.

The software captures and records each application invocation. The log data are anonymized and collected on a server through 3G networks. Each log record contains timestamp, anonymized user-id, and the package name of the application invoked.

The first invocation records are extracted for each application and each user. Figure 4 shows the cumulative number of extracted records from beginning of the experiment. The authors split the data set into a training set and a test set by timestamp. The training set consists of records gathered over 89 days (February – April 2011) and the test set consists of records collected over 31 days (May 2011) right after the training set. The authors excluded records of applications that had less than 3 unique users in the training set. This yielded 3383 records (155 users and 291 applications) in the training set and 249 records (98 users and 116 applications) in the test set. All of the adopted applications were free.

Figure 5 shows the number of applications adopted by users in the training set in descending order. Maximum number of applications adopted was 110. Table 2 shows the demographic distribution of contributing students and the statistics of adopted applications. Figure 6 shows the number of shared adopted applications for all user pairs in descending order.

3.2 Performance Measure and Evaluation Process

Influence matrix $R$ is estimated from the training set using Eq. (4). Approximated influence matrices $\hat{R}$ are calculated...
Table 2  Demographic distribution of participating students.

| Attributes       | # of Students | Avg. Adopted APs |
|------------------|---------------|-------------------|
| School           |               |                   |
| Letters          | 5             | 21.6              |
| Human Science    | 14            | 26.7              |
| Law              | 12            | 21.0              |
| Economics        | 13            | 38.5              |
| Science          | 7             | 24.9              |
| Medicine         | 23            | 25.7              |
| Pharma. Science  | 3             | 41.7              |
| Engineering      | 25            | 37.6              |
| Eng. Science     | 33            | 30.3              |
| Foreign Studies  | 19            | 22.4              |
| Others           | 1             | 13                |
| Entrance         |               |                   |
| 2007             | 3             | 29.0              |
| 2008             | 50            | 26.2              |
| 2009             | 28            | 34.5              |
| 2010             | 74            | 28.9              |
| Year             |               |                   |
| F                | 46            | 24.4              |
| M                | 109           | 31.0              |
| Sex              |               |                   |
| Total            | 155           | 29.1              |

Fig. 6  Number of shared applications adopted by each user pair in descending order.

Fig. 7  Perplexity of influence matrices with reduced ranks created by NMF.

Fig. 8  Perplexity of influence matrices with reduced ranks created by SVD and NMF.

3.3 Influencing Groups Discovered by Matrix Factorization

Figure 7 plots the operational optimal boundary in predictive performances on approximated influence matrices $\hat{R}$ with reduced ranks by NMF. We can observe certain decrease of perplexity (i.e., performance improvement) around remarkably small rank of 5 or 6. This implies that the inter-personal relationship has 5 or 6 latent components (or groups) structure and each user’s characteristic can be represented by weighting coefficients for these components.

Figure 8 plots the predictive performance results from the approximated influence matrix by SVD/NMF derived from the same data set used for Fig. 7. In any reduced rank, NMF demonstrates better perplexity than SVD. In the case of SVD, we observe worse perplexity than the original influence matrix used (which is 98.2635) over a wide range of reduced rank. It is notable that $\hat{R}$ by NMF retains its superior performance to the original $R$, although there is no guarantee that the approximation leads to a predictive performance improvement, supposedly as a result of the non-negativity constraint. Moreover, Fig. 8 also shows that smaller reduced ranks produced lower perplexity values on $\hat{R}$ by SVD as well as by NMF. This gives us another piece of evidence that supports the latent group structure in the inter-personal relationship.

Figure 9 visualizes the decomposed influence matrices at the lowest perplexity (reduced rank $k = 6$). The values
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Fig. 9  Heatmaps of decomposed influence matrices ($k = 6$).

Table 3  Inter-group / Intra-group influence.

| # of persons (proportion in %) | Influencing group where being influenced persons belong to |
|---------------------------------|----------------------------------------------------------|
|                                 | G1 | G2 | G3 | G4 | G5 | G6 |
| Influencing group               | G1 | 20 (51.3%) | 5 (12.8%) | 3 (7.7%) | 6 (15.4%) | 2 (5.1%) | 3 (7.7%) |
| where                           | G2 | 1 (3.2%) | 24 (77.4%) | 1 (3.2%) | 2 (6.5%) | 2 (6.5%) | 1 (3.2%) |
| influencing persons             | G3 | 2 (6.9%) | 0 (0.0%) | 11 (37.9%) | 4 (13.8%) | 10 (34.5%) | 2 (6.9%) |
| belong to                       | G4 | 0 (0.0%) | 2 (10.0%) | 3 (15.0%) | 7 (35.0%) | 2 (10.0%) | 6 (30.0%) |
|                                | G5 | 1 (5.9%) | 0 (0.0%) | 5 (29.4%) | 4 (23.5%) | 6 (35.3%) | 1 (5.8%) |
|                                | G6 | 1 (5.3%) | 1 (5.3%) | 9 (15.8%) | 0 (0.0%) | 6 (31.6%) | 8 (42.1%) |

of matrix elements are normalized by each user (the sum of elements is 1), and are expressed by color (red means high value, light yellow small value). Figure 9 (a) shows the coefficient matrix on influencing patterns and Fig. 9 (b) shows basis matrix representing the patterns of being influenced. Vertical (horizontal) axis represents individual users in the coefficient (basis) matrix. Vector of each user on the coefficient matrix denotes his/her influencing pattern, it indicates who are influenced by him/her. On the other hand, vector of each pattern (1 to 6 in this case) on the basis matrix shows the destination of influence. For example, pattern 1 means heavy influence is given to the 39 students at the left most columns of the basis matrix. Please note that those matrices are directional, i.e., influencing direction and being influenced direction. The matrix of Fig. 9 (b) can be considered as coefficient matrix of being influenced patterns, in such a case, Fig. 9 (a) is considered as a basis matrix as well.

Here, we can see each user has one dominant component according to Fig. 9 (a). The users who share the same dominant component in Fig. 9 (a) have similar influencing patterns. Let us call a group of users whose members share the dominant component (i.e. influencing pattern) an “influencing group”. On the same way, let us call a group of users whose members share dominant component in Fig. 9 (b) (i.e. being influenced pattern) an “influencee group”. A user belonging to influencing group G1 gives influence mainly to members of influencee group g1. Moreover, each user belongs to both of an influencing group and an influencee group. In other words, each member of influencee group g1 also belongs to one of influencing groups. Thus, we can calculate how strongly the members of influencing group G1 influence each influencing group. Based on the above consideration, the member proportions are shown in Table 3. That is, the table represents inter-group/intra-group influence proportion. According to Table 3, influence relationship among influencing groups can be roughly visualized as shown by Fig. 10. Table 3 shows that intra-group influence tends to occupy the major part. That means mutual influence among members within same influencing group is relatively dense. In addition, some of the inter-group influence relationships are also dense. Moreover, from Fig. 10, we can identify rough inter-group structures, i.e. G3–G6 are tightly linked while G1 and G2 are more independent from G3–G6.

Figure 1 is the result of applying graph structure visualization to $\hat{\mathbf{R}}$. Top 6% of influencing user–user relations were
Table 4  NMF algorithms contributing to Fig. 7 plots.

| Reduced Rank          | Best Algorithm                                      |
|-----------------------|-----------------------------------------------------|
| 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 | Non-smooth NMF based on Kullbach-Leibler divergence (nsNMF) |
| 25, 30, 35, 40, 45, 50, 60 | Pattern-Expression NMF based on Euclidean distance (PE-NMF) |

extracted from $\hat{R}$, where the sum of the extracted influencing factors occupies 35% of the grand total. A commonly used force-directed layout algorithm produced Fig. 1 from the extracted user–user relations with each node colored by identified influencing group mentioned above. It is obvious that Fig. 10 is fairly consistent in explaining the layout of Fig. 1.

3.4 Effects of Sparseness Control

Table 4 presents NMF algorithms which produced the best predictive performances plotted in Fig. 7. As we can see, the algorithm “nsNMF” performs the best in terms of perplexity for all dimensions lower than 20. “nsNMF” is an algorithm that focuses on controlling the sparseness on decomposed matrices while retaining its good approximation of the original matrix as well. This result shows that sparseness control is one of key factors in discovering the latent group structure of implicit influence.

“nsNMF” has one control parameter $\theta$ ($0 \leq \theta \leq 1$). $\theta = 1$ is the tightest sparseness constraint. With $\theta = 0$, the algorithm performs as ordinary NMF. Figure 11 shows predictive performances (perplexity) for different $\theta$ values. The curve is broad when $\theta = 0$ but becomes steep as $\theta$ increases. When $\theta$ exceeds 0.6, no drop in perplexity observed. Making decomposed matrices sparse means to narrow the ranges of people who influence / are influenced. This implies a mechanism similar to that of a resonant circuit. $\theta$ corresponds to the Q value of the circuit. With increased Q value ($\theta$) below an upper limit, the target characteristic becomes sharper. Since the dimension / rank has discrete value, it is reasonable that there be an upper bound in terms of Q value ($\theta$) where resonance can be observed.

3.5 Predictive Performance Comparison

Figure 12 shows predictive performances of the proposed latent feature model with varied reduced rank. As reference, performances of several popular recommendation techniques are also shown. In Fig. 12, “Latent Str. (NMF)” denotes the latent feature model discussed in the previous section. “Influence” denotes prediction based on $R$ without low rank approximation. “CF (User_COS)” denotes the conventional user-based CF based on cosine similarity. “Popularity” denotes simple prediction based on popularity, which is measured by the numbers of unique users in the training period. Similar to Fig. 7, we can observe a performance increase around $rank = 6$ for the latent feature model.

Figure 13 shows a performance comparison with various CF schemes. “CF (NMF)” uses a latent feature model which employs NMF for matrix factorization. “CF
(SVD_bias)” and “CF (SVD++)” are SVD-based CFs [25] and are known to be high performers for movie rating prediction. “CF (wALS_item)”、“CF (wALS_user)” and “CF (wALS_universal)” are specialized CFs for the one-class setting [24]. Here, it should be noted that the task under discussion is one-class setting, where no negative samples are available for training. Thus “CF (NMF)”, “CF (SVD_bias)” and “CF (SVD++)” were trained and tested with AMAN (all missing as negative) strategy.

As we can see, the proposed latent feature model demonstrates the best performance, slightly higher than “wALS_item”. This result validates the proposed model and its usefulness for personalized recommendations as one of its applications.

4. Discussion

4.1 Latent Group Characteristics

The latent groups (influencing groups and influencee groups) are formed by similar influencing / being influenced patterns. This implies that the group members tend to have similar application usage behavior and demographic attributes. This motivated us to perform an analysis of demographics / application usage and influencing groups.

Some demographic analysis results are shown in Table 6. Some degree of correlation was observed for schools and sex. The top 20 most-frequently-used applications in each influencing group are listed in Table 7. Since the number of groups was selected by best predictive performance and not for better topic separation, it is hard to find concrete topics or characteristics on application preferences for each influencing group. Some symbolic applications can be found such as medicine search application in G4 to which many students of the medicine school belong.

4.2 Correlation Analysis with Other Factors

If some user attributes exhibit strong correlation with implicit influence, they could contribute to the improvement in predictive performance. Thus, the authors conducted a correlation analysis on influence factors with some user attributes. All user pairs were classified into two groups depending on whether both users have same attribute or not. Then correlation ratios were calculated between the groups. Tested attributes were school, entrance year, community, and whether the number of adopted applications is higher/lower than average. Here, community means a group of friends, as mentioned in Sect. 3.1.

The results are shown in Table 5. No obvious correlation was observed on any attributes except acquired influencing groups. This implies that it is difficult to infer implicit influencing relationship by such attributes.

4.3 Visualizing Approximation Magnitude

From viral marketing point of view, it is valuable to identify persons who are opinion leaders that influence their surroundings, in order to make targeting strategies more effective. Here, each user’s degree of influence, influenciality, and susceptibility to influence, influenceability, can be defined as follows:

\[
\text{influentiality}_u = \frac{\sum P_r(u \rightarrow v)}{U_{\text{exp}} - 1}, \quad \text{and} \quad (5)
\]

\[
\text{influenceability}_u = \frac{\sum (P_r(v \rightarrow u))}{U_{\text{exp}} - 1}. \quad (6)
\]

Figure 14 shows a scatter plot of influentiality versus influenceability calculated from the original influence matrix \( \mathbf{R} \) and the approximated influence matrix \( \mathbf{\hat{R}} \) with the best predictive performance. Each plot corresponds to an individual user. Arrows show how much the approximation changes user position. We can see that there is no obvious correlation in distribution between influentiality and influenceability. We can also see several outliers. In the case of users who used few applications, the values of \( P_r(u \rightarrow v) \) becomes unstable. This intuitively explains the

| Table 5 Correlation ratios. |
|-----------------------------|
| Factor                      | Correlation ratio | \( \mathbf{R} \) | \( \mathbf{\hat{R}} \) |
|-----------------------------|-------------------|-----------------|-----------------|
| User pair in Same School vs others | 0.020142          | 0.017418        |
| User pair in Same Grade vs others | 0.006050          | 0.001535        |
| User pair in Same Community vs others | 0.019159          | 0.018326        |
| Pair of Heavy Users vs others | 0.068715          | 0.098507        |
| Pair of Light Users vs others | 0.063818          | 0.078679        |
| User pair in Same Influencing Gr. vs others | 0.092977          | 0.208375        |

| Table 6 Demographic distribution of influencing groups. |
|-------------------------------------------------------|
| Influencing Group | Letters | Human Science | Law | Economics | Science | Medicine | Pharmaceutical Sciences | Engineering | Engineering Science | Foreign Studies | Others | Sex | Total |
|-------------------|---------|---------------|-----|-----------|---------|----------|------------------------|-------------|----------------------|---------------|--------|-----|--------|
| G1                | 1       | 3             | 2   | 2         | 1       | 5        | 1                      | 4           | 3                    | 3             | 0      | 11  | 14    | 25    |
| G2                | 1       | 6             | 3   | 2         | 1       | 3        | 1                      | 3           | 6                    | 6             | 0      | 10  | 22    | 32    |
| G3                | 2       | 1             | 2   | 0         | 3       | 1        | 4                      | 10          | 1                    | 1             | 2      | 4   | 24    | 26    |
| G4                | 0       | 0             | 2   | 3         | 0       | 8        | 0                      | 1           | 6                    | 3             | 0      | 10  | 13    | 23    |
| G5                | 1       | 2             | 1   | 4         | 2       | 3        | 0                      | 8           | 4                    | 3             | 0      | 5   | 23    | 28    |
| G6                | 0       | 2             | 2   | 0         | 3       | 0        | 5                      | 4           | 3                    | 0             | 8      | 13  | 21    | 35    |
| Total             | 5       | 14            | 12  | 13        | 7       | 23       | 5                      | 25          | 35                   | 19            | 1      | 46  | 109   | 155   |
Table 7: Popular applications in influencing groups.

| Rank | G1                          | G2                          | G3                          | G4                          | G5                          | G6                          |
|------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| 1    | com.android. calculator2    | Android                     | com.android. inputmethod.latin | com.cookpad. android.activities | com.cooliris.media         | com.google.android. voicesearch |
| 2    | com.android. inputmethod.latin | com.google.android.providers. enhancedgoogle.search | net.binzume. android. nicoplayer | com.fox. mail               | com.android. packageinstaller | com.android. basicwords     |
| 3    | com.facebook. katana       | com.sonyericsson. alarmclock | com.android. activities     | cn.bluekey. neatreversi     | com.android. wallpaper.livepicker | com.mobisystems. office     |
| 4    | com.mobisystems. office     | com.sonyericsson. conversations | com.android. packageinstaller | jk.co.gnavi.activity       | com.androidспект. katana    | com.sonyericsson. pccompanion |
| 5    | com.sonyericsson. quadrapop | com.android. browser         | com.google.android. youtube | com.android. calculator2    | com.google.android. voicesearch | com.sonyericsson. quadrapop |
| 6    | com.android. vending       | com.google.android. youtube | com.pdanet                  | com.android. xing. client.android | com.sprintmobile. backup.senc | com.sprintmobile. backup.senc |
| 7    | com.cooliris.media         | com.android. phone           | com.skype. raider            | com.sonyericsson. services | com.sonyericsson. quadrapop | com.android. calculator2   |
| 8    | com.sonyericsson. android.basicwords | com.google.android. apps.maps | com.adobe. reader           | com.sonyericsson. quadrapop | com.nttdocomo. compass       | com.sonyericsson. calculator2 |
| 9    | com.sonyericsson. android.iwanime | com.mobisystems. office     | android calculator          | de. joergjahnke. mario.android. free | com.sonyericsson. android.friendpivot | com.cooliris.media      |
| 10   | com.sonyericsson. android. servicemenu | com.sonyericsson. android.camera | com.android. rendezvous       | com.sonyericsson. android. wallpaperchooser | com.android. finder         | com.sonyericsson. katana   |
| 11   | com.sonyericsson. setupwizard | com.sonyericsson. android.mediascape | com.evernote               | com.sonyericsson. webmomo    | com.sonyericsson. pccompanion | com.google.android. street  |
| 12   | com.android. globalsearch  | com.sonyericsson. android. socialaphonebook | com.google. coordination | nikeno.Tenki                | jpssoft. apps. mysettings   | com.sonyericsson. talk      |
| 13   | com.android. wallpaper.livepicker | com.android. launcher       | com.nttdocomo. android.compass | war.Weathernews Touch.jp    | com.adobe. reader           | com.nttdocomo. android.compass |
| 14   | com.nttdocomo. android. docomo_market | com.google. android.gm     | com.sonyericsson. textinput.uxp | com.android. alarmclock     | com.android. alarmclock     | com.sakura. News2010       |
| 15   | com.sonyericsson. android. socialservicestting | com.sonyericsson. search   | jk.busterc. virtualtenho_g  | com.android. alarmclock     | com.android. alarmclock     | com.sonyericsson. android. servicemenu |
| 16   | com.sonyericsson. pccompanion | com.android. settings       | jk.radiko. gui.main          | com.android. globalsearch   | com.android. Htmlviewer     | com.sonyericsson. serviceiphone |
| 17   | com.sonyericsson. textinput.uxp | com.android. vending       | org.ad. launcher             | com.android. providers. applications | com.bumptech. bumpgafa      | com.sonyericsson. trackid3.client |
| 18   | com.android. alarmclock    | com.google.android. voicesearch | asa.sonix. sekaimeigenwitz   | com.bumptech. bumpgafa      | com.clapfootgames. tankhero | de.shandshuh. sparsers    |
| 19   | com.android. calendar      | com.sonyericsson. android. friendpivot | com.android. phone           | com.ekitan. android         | com.donpon. pisces. cashbook  | com.co.c2inc. medicalite.first |
| 20   | com.cooltek. touchpal     | com.sonyericsson. android.playnow | com.android. providers. applications | com.google. android. location | com.fgol. sharkfree        | com.co.labelgate. moratouch   |

appearance of the outliers.

Influentiality and influenceability above are based on implicit influences, thus they reflect tendency effects as mentioned in Sect.1. Therefore, a user with high influentiality does not necessarily mean a real opinion leader. The authors leave this accuracy issue for future work. Identifying opinion leaders may require further analytical studies.

5. Conclusion

This paper described an algorithmic approach that can discover implicit influencing group structures of social influence among users in terms of smartphone application usage. The method utilizes nonnegative matrix factorization with a sparseness constraint. Latent user groups were experimentally identified by observing predictive performance against reduced dimensions of the influence matrix. Analysis found the influencing relationships, which consist of intra-group influence and inter-group influence. Moreover, the model successfully predicted students’ application downloads from their past activities; a MAP evaluation showed that it attained better performance than state-of-the-art and conventional collaborative filtering methods, as well
as a popularity method.

Future studies should examine more sophisticated diffusion models to enhance performance. Scalability and adaptability are key goals to be tackled. Since influencing relationships depend on the topic, model extension for topic-based is also worth tackling.

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