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Z. Guo, K. Yu, T. Guo, A. K. Bashir, M. Imran and M. Guizani, "Implicit Feedback-based Group Recommender System for Internet of Things Applications," *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, 2020, pp. 1-6.

Available online: https://doi.org/10.1109/GLOBECOM42002.2020.9348091

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# Implicit Feedback-based Group Recommender System for Internet of Thing Applications

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Abstract-With the prevalence of Internet of Things (IoT)based social media applications, the distance among people has been greatly shortened. As a result, recommender systems in IoTbased social media need to be developed oriented to groups of users rather than individual users. However, existing methods were highly dependent on explicit preference feedbacks, ignoring scenarios of implicit feedbacks. To remedy such gap, this paper proposes an implicit feedback-based group recommender system using probabilistic inference and non-cooperative game (GREPING) for IoT-based social media. Particularly, unknown process variables can be estimated from observable implicit feedbacks via Bayesian posterior probability inference. In addition, the globally optimal recommendation results can be calculated with the aid of non-cooperative game. Two groups of experiments are conducted to assess the GREPING from two aspects: efficiency and robustness. Experimental results show obvious promotion and considerable stability of the GREPING compared to baseline methods.

Keywords—Internet of Things, group recommender systems, implicit feedback, probabilistic inference

# I. INTRODUCTION

In the Internet of Things (IoT), recommender systems (RS) have become effective tools to deal with information overload issue in its social media applications. The main aim of RS in IoT-based social media is to suggest suitable items for users in accordance with their preference feedbacks. Accompanied with the growing popularity of various IoT-based social media like crowdsensing applications, people have been more connected. A huge number of online social activities begins to be carried out in groups. To this end, group recommender systems (GRS), recommending items to groups of users rather than individual users, have been a novel concern in this field.

As preference features of members in a group are usually diversified, how to balance their interest conflicts remains a challenging task. Existing solutions concerning GRS can be classified into two categories: preference aggregation-based approaches [1]-[9] and score aggregation-based approaches [10]-[19]. The former aggregate preference feedbacks (e.g. preference ratings) of members into preference feedbacks of a group. While the latter directly aggregate recommendation lists of members as the results for a group. However, almost all of them were established upon the situations where preference feedbacks are explicit. They cannot work well when it comes to scenarios of implicit preference feedbacks. In contrast to explicit feedbacks, the implicit ones (e.g. click records, search records, etc.) indirectly express preference degree of users, and are actually a type of data form widely existing in realistic world.

To tackle with this challenge, in this paper, a Group **Re**commender system through **P**robabilistic Inference and **N**oncooperative **G**ame (GREPING) is proposed for IoT-based social media applications. Specifically, this research introduces probabilistic inference model to estimate quantified preference features from implicit feedbacks, and generates globally optimal recommendation results that satisfy as many members as possible. In addition, this research implements two groups of experiments to evaluate both efficiency and robustness of the proposed GREPING. Results reflect good performance of the GREPING with respect to those two aspects.

The rest of this paper is organized as follows. In section II, we describe the general situation of the research problem, and present the system architecture of the GREPING. Section III demonstrates the detailed procedures of the methodology. Experimental evaluations are illustrated in Section IV. Finally, we conclude the paper in Section V.



Fig. 2 System Architecture of the proposed GREPING.

# II. PROBLEM STATEMENT

Let a set of users  $B = \{u_1, u_2, \dots, u_{|G|}\}$  constitute a group G whose size is |G|, and a set of items  $V = \{v_1, v_2, \dots, v_Q\}$  constitute the training set. The behavior of member  $u_i(i = 1, 2, \dots, |G|)$  selecting or consuming an item is defined as an interaction between user  $u_i$  and item  $v_j$ . Suppose that each item is associated with some descriptive text and can be assigned a topic indicator  $z_j = k(k = 1, 2, \dots, K)$  according to textual information, and that another set of items  $V' = \{v'_1, v'_2, \dots, v'_T\}$  constitute the candidate set to be selected as recommendation results. At the same time, above problem scenarios are set up on the basis of following assumptions:

*Assumption 1:* Social relationships exist among members of Group *G*, and will impact preference features of users.

*Assumption 2:* All behavior records are independent of others, and there are no sequential correlations among them.

*Assumption 3:* Generation of behavior results of group members mainly depends on two variables: inherent preference and social confidence which are defined as:

**Definition 1 (Inherent Preference):** Regardless of social factors, initial preference of one user towards an item is defined as his inherent preference.

**Definition 2 (Social Confidence):** When a member makes a decision, the combined influence received from all other members is defined as his social confidence.

System architecture of the proposed GREPING is illustrated in Fig. 2, containing three main components: topic classification preprocessing, process variable inference, and recommendation generation. The first one mainly assigns a topic indicator to each item according to their text via Twitter-LDA algorithm [20]. The second one estimates unknown process variables through probabilistic inference. The third one manages to calculate globally optimal recommendation results for social groups to maximize utility of heterogeneous members.

#### III. METHODOLOGY

#### A. Inference of Hidden Variables

In a social group G, selection decision of user  $u_i$  towards item  $v_i$  majorly depends on the following aspects of factors: 1)



Fig. 1 Graphical template for generative process of behavior decisions.

topic indicator of the item  $z_j$ ; 2) inherent preference  $I_{k,i}$  of user  $u_i$  towards k-th topic; 3) contribution rate of topic k towards user  $u_i$ ; 4) social confidence  $S_{k,i}$  of user  $u_i$  towards k-th topic.

Based on the above analysis, selection decision of user  $u_i$  towards item  $v_j$  is generated through the intermediate process illustrated in Fig. 1. Inherent preference  $I_{k,i}$  of user  $u_i$  is assumed to satisfy Gaussian distribution with mean  $\mu_1$  and variance  $\sigma_1^2$ , namely,  $I_{k,i} \sim \mathcal{N}(\mu_1, \sigma_1^2)$ . And social confidence  $S_{k,i}$  of user  $u_i$  is assumed to satisfy another Gaussian distribution with mean  $\mu_2$  and variance  $\sigma_2^2$ , namely,  $I_{k,i} \sim \mathcal{N}(\mu_2, \sigma_2^2)$ . Decision result  $d_{j,i}$  of user  $u_i$  towards item  $v_j$  is represented as:

$$d_{j,i} = \begin{cases} 1, & \text{user } u_i \text{ selects item } v_j \\ 0, & \text{user } u_i \text{ never selects item } v_j \end{cases}$$
(1)

For scenes where  $d_{j,i} = 1$ , given topic indicator  $z_j$  of item  $v_j$ , conditional probabilistic expression of generative process is deduced through logistic function as:

$$\mathcal{P}(d_{j,i} = 1 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) = \frac{1}{1 + \exp(-\pi_{k,i}I_{k,i} - S_{k,i})}$$
(2)

where  $\pi_{k,i}$  is the contribution rate of topic k towards user  $u_i$  and represented as:

$$\pi_{k,i} = \frac{n_i^{(k)}}{n_i} \tag{3}$$

where  $n_i$  is total number of interactions from user  $u_i$ , and  $n_i^{(k)}$  is total number of interactions from user  $u_i$  concerning k-th topic. Obviously, the probability that user  $u_i$  selects item  $v_j$  is proportional to variables  $\pi_{k,i}$ .

For scenes where  $d_{j,i} = 0$ , conditional probabilistic expression of generative process is deduced as:

$$\mathcal{P}(d_{j,i} = 0 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) = 1 - \frac{1}{1 + exp(-\pi_{k,i}I_{k,i} - S_{k,i})}$$
(4)

The joint conditional probability of  $d_{j,i}$  is deduced as:

$$\mathcal{P}(d_{j,i}|z_{j}, \pi_{k,i}, I_{k,i}, S_{k,i})$$

$$= \left[\mathcal{P}(d_{j,i} = 1|z_{j}, \pi_{k,i}, I_{k,i}, S_{k,i})\right]^{\delta(d_{j,i},1)} (5)$$

$$\cdot \left[\mathcal{P}(d_{j,i} = 1|z_{j}, \pi_{k,i}, I_{k,i}, S_{k,i})\right]^{[1-\delta(d_{j,i},1)]}$$

where  $\delta(a, b)$  is Kronecker delta.

Therefore, the joint probabilistic expression of  $d_{j,i}$ ,  $\pi_{k,i}$ ,  $I_{k,i}$  and  $S_{k,i}$  can be deduced as:

$$\mathcal{P}(d_{j,i}, \pi_{k,i}, I_{k,i}, S_{k,i} | z_j, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2) = \mathcal{P}(I_{k,i} | \mu_1, \sigma_1^2) \cdot \mathcal{P}(S_{k,i} | \mu_2, \sigma_2^2) \quad (6) \\ \cdot \mathcal{P}(d_{j,i} | z_j, \pi_{k,i}, I_{k,i}, S_{k,i})$$

And loss function can be constructed according to Eq. (6) as:

$$\begin{aligned} \mathcal{J}_{j,i} &= -\log \mathcal{P} \big( d_{j,i} \big| z_j, \pi_{k,i}, I_{k,i}, S_{k,i} \big) \\ &- \log \mathcal{P} \big( I_{k,i} \big| \mu_1, \sigma_1^2 \big) \\ &- \log \mathcal{P} \big( S_{k,i} \big| \mu_2, \sigma_2^2 \big) \end{aligned} \tag{7}$$

According to definition of Gaussian distribution, the above formula can be further approximated as:

$$\begin{aligned} \mathcal{J}_{j,i} \\ &\propto -\delta(d_{j,i}, 1) \log \mathcal{P}(d_{j,i} = 1 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) \\ &- \left[ 1 - \delta(d_{j,i}, 1) \right] \log \mathcal{P}(d_{j,i} = 0 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) \\ &- \frac{\left( I_{k,i} - \mu_1 \right)^2}{2\sigma_1^2} - \frac{\left( S_{k,i} - \mu_2 \right)^2}{2\sigma_2^2} \end{aligned}$$
(8)

Having established the learning objective, a universal learning scheme named stochastic gradient descent (SGD) is selected here to search for optimal solutions. The SGD seeks out minimum of the objective function through calculating partial derivatives of parameters and updates them iteratively to reduce the empirical error. Thus, partial derives with respect to  $I_{k,i}$  and  $S_{k,i}$  at the *g*-th round iteration can be respectively calculated as:

$$\begin{pmatrix} \frac{\partial \mathcal{J}_{j,i}}{\partial I_{k,i}} \end{pmatrix}^{(g)} = \pi_{k,i} \delta(d_{j,i}, 1) - \pi_{k,i} \mathcal{P}(d_{j,i} = 1 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) \quad (9) + \frac{I_{k,i} - \mu_1}{\sigma_1^2} \begin{pmatrix} \frac{\partial \mathcal{J}_{j,i}}{\partial S_{k,i}} \end{pmatrix}^{(g)} = \delta(d_{j,i}, 1) - \mathcal{P}(d_{j,i} = 1 | z_j, \pi_{k,i}, I_{k,i}, S_{k,i}) \quad (10) + \frac{S_{k,i} - \mu_2}{\sigma^2}$$

Iterative processes in SGD can be expressed as:

$$I_{k,i}^{(g+1)} = I_{k,i}^{(g)} - \theta \cdot \left(\frac{\partial \mathcal{J}_{j,i}}{\partial I_{k,i}}\right)^{(g)}$$
(11)

$$S_{k,i}^{(g+1)} = S_{k,i}^{(g)} - \theta \cdot \left(\frac{\partial \mathcal{J}_{j,i}}{\partial S_{k,i}}\right)^{(g)}$$
(12)

#### B. Generation of Recommendation Results

This subsection analyzes cooperation and competition mechanisms among group members and builds a noncooperative game model to coordinate the item allocation of the whole group. Three aspects of elements included in game process are defined as follows:

**Definition 3 (Player Set):** Members of a group constitute players in a game, and the size is |G|.

**Definition 4 (Strategy Set):** Suppose that player  $u_i$  is required to select one from K topic indicators as his game strategy  $s_i$ . Strategy set of all the |G| players is represented as:

$$\Omega = \left\{ s_1, s_2, \cdots, s_{|G|} \right\} \tag{13}$$

**Definition 5 (Utility Set):** Each player  $u_i$  can acquire a utility  $U_i$  according to contents of the strategy set  $\Omega$ . Utility set of all the |G| players is represented as:

$$U = \{U_1, U_2, \cdots, U_{|G|}\}$$
(14)

In order to deduce utility expression, variables  $I_{k,i}$  and  $S_{k,i}$  need to be normalized into the range of [0,1], leading to  $I'_{k,i}$  and  $S'_{k,i}$ . Given strategy  $s_i$ , profit possibly obtained by player  $u_i$  can be quantified as:

$$r_i = \frac{E(s_i)}{Y(s_i)} = \frac{s_i \cdot \rho_{s_i}}{Y(s_i)}$$
(15)

where  $E(s_i)$  is the expectation of strategy  $s_i$  selected by player  $u_i$ ,  $Y(s_i)$  is the total number of players who select  $s_i$  as their strategies, and  $\rho_{s_i}$  equals  $I'_{s_i,i}$ . On the other hand, player  $u_i$  must also bear a certain cost in terms of selecting strategy  $s_i$ , which is represented as:

$$c_i = \lambda_1 \left( S'_{s_i,i} + 1 - I'_{k,i} \right)^{\iota}$$
(16)

where  $\tau$  is exponential parameter. Thus, total utility of player  $u_i$  can be deduced as:

$$U_{i} = \lambda_{2} (r_{i} - s_{i}c_{i})$$
  
=  $\lambda_{2} \left\{ \frac{s_{i} \cdot \rho_{s_{i}}}{Y(s_{i})} - s_{i} \cdot \lambda_{1} \cdot \left( S_{s_{i},i}' + 1 - I_{k,i}' \right)^{T} \right\}$  (17)

where  $\lambda_1$  and  $\lambda_2$  are trade-off parameters.

It is assumed that  $\Omega^* = \{s_1^*, s_2^*, \dots, s_{|G|}^*\}$  denotes the strategy set of all the players when Nash equilibrium is reached. Therefore, solutions under Nash equilibrium status can be obtained by letting the following formula equaling to 0. After obtaining  $\Omega^*$ , recommendation results for group *G* can be represented as:

$$\mathcal{L}_G = \left\{ \mathcal{O}_1, \mathcal{O}_2, \cdots, \mathcal{O}_{|G|} \right\}$$
(18)

where  $O_k$  is the ratio of items assigned with topic indicator k. Form of recommendation results are ratios of each topic indicator in  $\Omega^*$ , rather than specific items.

TABLE I Statistical Characteristics of Datasets

STATISTICAL CHARACTERISTICS OF DATASETS		
Indexes	Last.fm dataset	Delicious dataset
Number of users	1628	1542
Number of items	14926	57643
Number of interactions	74169	85217
Number of groups	108	76
Average social density	0.36	0.33
Average group size	29.6	33.2
Average length of text per item	47.5	36.8



Fig. 4 Real and predicted values of topic distributions with respect to different methods (Delicious dataset).

# IV. EXPERIMENTS AND ANALYSIS

#### A. Datasets and Pre-processing

In this experiment, two standard datasets Last.fm<sup>1</sup> and Delicious<sup>2</sup> in area of social recommendations are used to construct simulation scenarios. However, the two datasets contain no group information, and there are still no datasets released publicly for researches of group recommendations. In our experiments, groups are constructed through two rules:

- Inactive users in the original datasets (i.e. individuals with little interaction) are supposed to be filtered out.
- Social density of a group is defined as:

$$\mathcal{D}_G = \frac{2\mathcal{A}_G}{|G| \cdot |G-1|} \tag{19}$$

where  $\mathcal{A}_G$  is the number of social relationships of group *G* which are observable. Thus, social density of a constructed group is required to retain higher than 0.25. Statistical characteristics of the final datasets are listed as TABLE I.

# **B.** Experimental Settings

It is expected to measure distance between predicted proportion distributions and real proportion distributions of all topics. Measurement of distance error is realized through six evaluation metrics: Euclidean distance, Chebyshev distance, Manhattan distance, correlation distance, mean absolute error (MAE) and mean square error (MSE). And three representative methods: **ConfiMF** [21], **ContextMF** [22] and **RanGroup** [23], are selected for comparisons.

As for Last.fm dataset, prior parameters  $\mu_1$ ,  $\sigma_1^2$ ,  $\mu_2$  and  $\sigma_2^2$  are initially set to 45, 70, 12 and 30 by default. As for Delicious

dataset,  $\mu_1$ ,  $\sigma_1^2$ ,  $\mu_2$  and  $\sigma_2^2$  are initially set to 45, 75, 10 and 25 by default. Learning rate and convergence threshold in SGD are set to 0.01 and 0.001 respectively. At stage of recommendation generation, trade-off parameters  $\lambda_1$  and  $\lambda_2$  are set to 0.6 and 0.4 respectively. Concerning division of training set and testing set, proportion of training data is set to 70% initially. Number of topic is set to 6 in Last.fm dataset, and 10 in Delicious dataset.

#### C. Results and Analysis

Fig. 3 and Fig. 4 visualize predicted proportion distributions and real proportion distributions of all the topics. Both of them are made up of four subfigures, corresponding to four experimental methods. It can be intuitively observed from these figures that performance of the proposed GREPING exceeds ConfiMF, because distance error between predicted and real topic distributions of GREPING is obviously smaller. But as performance comparison between GREPING and the other two baselines cannot be directly observed from these figures, six quantified evaluation metrics are introduced for assessment.

Experimental results concerning six evaluation metrics are illustrated in Fig. 5. It can be clearly observed that results of GREPING method on two datasets are better than baselines. Although ContextMF and RanGroup take social contextual information into account, they just simply model association rules among behaviors and fail to explore more fine-grained influential factors such as inherent preference and social confidence. Conversely, the proposed GREPING integrates multiple-source features from individuals and groups, thus enhancing depth of feature extraction. In a word, deep feature inference is possibly the key power to promote implicit feedback-based social recommendations.

Apart from relatively ideal experimental results, the GREPING also pays some price in terms of time complexity.

<sup>&</sup>lt;sup>1</sup> https://www.last.fm/

<sup>&</sup>lt;sup>2</sup> https://www.delicious.com



Particularly, time complexity is as  $C(200 \cdot K \cdot n)$  at the stage of Twitter-LDA, as  $\mathcal{C}(|G| \cdot K \cdot Q \cdot n_q)$  at stage of process variable inference, and as  $\mathcal{C}(|G| + |G| \cdot K)$  at the stage of recommendation. Among, n is the number of words, and  $n_a$  is the number of iterative rounds. Thus the total time complexity of GREPING can be simplified as  $C(|G| \cdot K \cdot Q \cdot n_q + 200 \cdot K \cdot Q)$ n), which is more complicated than that of baselines. We further conduct a group of experiments to evaluate stability of the GREPING by testing its parameter sensitivity. Firstly, parameter sensitivity of  $\mu_1$  and  $\sigma_1^2$  are explored when the other two parameters are set to default values. Then, parameter sensitivity of  $\mu_2$  and  $\sigma_2^2$  are visualized with other parameters setting to their default values. This group of experiments singly explore

sensitivity of GREPING, without making comparisons with baselines. In addition, Euclidean distance is utilized for assessment in this group of experiments. Accordingly, experimental results on two datasets are respectively illustrated in Fig. 6 and Fig. 7. It can be observed from these figures that most of areas in these figures are in blue color and never have sharp color changes. This phenomenon reveals that GREPING is robust to parameter changes and has good stability. This is because GREPING recovers hidden process variables and exploits non-cooperative game to ensure a comprehensive insight for recommendation generation.

(c) Manhattan distance

(f) MSE

μ,

μ,

To sum up, two aspects of conclusions can be deduced from the above experiments. For one thing, the proposed GREPING is able to well tackle with the implicit feedback-based social recommendation problem. Because it comprehensively considers two constructive problems: hidden feature extraction and optimal resource allocation. For another, the proposed GREPING is an unsupervised method, but is not easily influenced by parameter changes.

# V. CONCLUSION

With the increasing visibility of IoT-based social media, recommending items to groups of users rather than individual users has been a more common demand. Existing research was mostly developed towards explicit feedback-based situations, ignoring implicit preference feedbacks. This paper proposes a group recommender system through probabilistic inference and non-cooperative game (GREPING) for IoT-based social media. The proposed GREPING is composed of two main parts: process variables inference and recommendation results generation. The former estimates unknown intermediate process variables through probabilistic inference, and the latter calculates the globally optimal recommendation results via noncooperative game. Finally, a series of experiments are conducted to evaluate both efficiency and stability of the proposed GREPING.

# ACKNOWLEDGMENT

This work was supported by the Chongqing Natural Science Foundation of China under grant cstc2019jcyj-msxmX0747, State Language Commission Research Program of China under grant YB135-121, National Natural Science Foundation of China under grant 61901067, and Japan Society for the Promotion of Science (JSPS) Grants-in-Aid for Scientific Research (KAKENHI) under Grant JP18K18044.

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