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Collaborative Filtering for Recommendation of Areas in Virtual Worlds

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***Abstract*— Collaborative filtering (CF) is a class of recommendation methods that have been used in web contents such as video sites and electronic-commerce sites. To our knowledge, CF, however, has not been used in three-dimensional virtual worlds yet. In this paper, we verify the applicability of two state-of-the-art CF methods in a three-dimensional virtual world called Second Life (SL). Our experiment results on data from SL verify that CF methods can also be applied to area recommendation in virtual worlds. A discussion on which CF method should be used in this application domain is also given.**

***Keywords*— Virtual World; Second Life; Recommendation; Collaborative Filtering**

I. INTRODUCTION

In recent years, recommender systems that select and present useful products and information for their users have become very popular. So far, they have been mainly used in the 2D or flat web spaces such as YouTube or Amazon. However, recommender systems for 3D environments or virtual worlds, such as Second Life (SL)[1], are still rare. Virtual worlds have attracted much attention in recent years because they simulate real world situations or locations and provide potential platforms for various applications. There is, however, an important yet unsolved issue that it is difficult to find the areas that suit the users from among rich virtual world contents.

In this study, we aim to solve the above issue by applying recommender systems to virtual worlds. In previous work, Eno et al. [1] developed recommender systems for virtual worlds SL and OpenSimulator using content-based filtering. In our study, we adopt another recommender approach called collaborative filtering (CF). Content-based filtering recommends other items whose features are similar to those of the items which a user of interest has evaluated. On the contrary, in CF, the recommender accumulates behaviors that express the preference of a user of interest first. Then, it makes recommendations by using the information of other users having similar preferences to the user. Typical CF techniques do not use such features, whose information must be given in advance. This leads to an advantage that CF can give recommendations to the users by utilizing only the information on the items evaluated previously by those users.

This work reports the first phase of our project in which we plan to develop a recommender system in SL that recommend its users areas they should visit next. The findings here can also be applied to other online games such as massively multiplayer online role-playing games. The rest of this paper is organized as follows. In Section 2, we describe SL. Section 3 presents the state-of-the-art CF methods that are used in our study. In Section 4, we show the evaluation results. Our conclusions and future work are reported in Section 5.

II. SECOND LIFE VIRTUAL WORLD

In this section, we describe more details about SL. SL is one of the largest virtual worlds with more than 25000 unique areas and about 100 million users. SL users enjoy their experiences in SL by manipulating their avatars as their alter egos to visit various areas, create contents or interact with other users.

Due to the advent of the richness in contents and information, SL has been utilized for many research purposes. In the study of Eno et al. [1], they created crawling bots to collect data from SL and performed experiments with content-based filtering on the crawled data. Steurer et al. [2] conducted an analysis of the social network of SL users using data crawled from SL. Varvello et al. [3] proposed a method for avatar bot detection in SL.

In order to obtain the necessary data for our experiments, we also created crawling bots in SL and collected the SL users' information for the average of 22 days per bot. Data collection was performed by making two-or-more-area patrols up to 20 crawler bots. By this crawling, we collected the information on which users visited which areas using

[1] Second Life http://secondlife.com/

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their avatars. The crawling results are summarized in Table I. In this table, "#users" and "#areas" indicate the number of users and that of areas while "#non-zeros" represents the number of non-zero elements, in the user-area matrix, that are 1 when the corresponding user visited the corresponding area, otherwise 0; and the sparseness is the ratio of the zero elements in the user-area matrix. In our work, we assume that every user only visits the areas that s/he only has an interest in. In our experiments, we apply two state-of the-art CF methods, discussed below, to the collected data in order to verify their performances in recommending areas in SL.

TABLE I. CRAWLING DATA FROM SECOND LIFE

#users	287202
#areas	1402
#non-zeros	800820
sparseness	99.80%
avg. visiting areas per user	2.79

III. COLLABORATIVE FILTERING

CF is a recommendation approach based on the idea that users who had similar preference on items in the past may also have similar preference in the future. In the recommendation domain, the users' preference is often evaluated based on their explicit feedbacks on the available items. However, in SL, we could not readily obtain such a feedback like the rating information for the visited areas. Therefore, we decided to use the information on whether they visited the given areas in the past as our implicit feedback to evaluate the users' preference. In the case of commodity recommendation, the preference degree of an item can be assumed to be "the purchased items' preference > the unpurchased items' preference" [4]. In this case, regardless of the number of purchases, the evaluation value of a purchased item is set to 1 while that of an unpurchased item to 0. In our area recommendation task in virtual worlds, following the same recipe, we define the evaluation value to a visited area to 1 and that of an unvisited area to 0. The methods we used in our experiments are Bayesian Personalized Ranking-Matrix Factorization (BPR-MF) and Collaborative Less-is-More Filtering (CLiMF). They are currently state-of the-art CF methods that use a matrix factorization (MF) technique [5] and are known suitable for recommendation problems with implicit feedback data.

A. Matrix Factorization

MF is a dimensionality reduction method commonly used in the recommendation domain. In this method, the task is to find two smaller matrices whose product is an approximation of the original matrix. These matrices indicate the relationship between the users/items and the latent factors. MF recently became famous due to recommender systems using it having high performance in the Netflix competition, in which submitted recommender entries compete one another for the recommendation accuracy.

B. Bayesian Personalized Ranking-Matrix Factorization

Rendle et al. [4] proposed this method. BPR-MF is the CF method that maximizes a posteriori (MAP) estimation of the model parameters. BPR-MF is based on the assumption that users prefer relevant items (evaluated items or visited areas in our study) than irrelevant items. The objective function of the method represents the smoothed Area under the curve (AUC). In BPR-MF, MF is used in the prediction model.

C. Collaborative Less-is-More Filtering

CLiMF, proposed by Yue et al. [6], is the CF method that optimizes the objective function represented by smoothing the mean reciprocal rank (MRR), whose description is given in Section IV-A. This method can also cope with the implicit feedback data as in the BPR-MF method. In CLiMF, MF is also used in the prediction model.

IV. EVALUATION

In this section, we verified if CF techniques can be applied to recommendation in virtual worlds, as it does in real-world recommendation applications. In addition to BPR-MF and CLiMF, described above, we used PopRec as our baseline recommender. PopRec is a naive approach that recommends items ranked according to their popularity, the number of visits by unique users.

A. Dataset

We used the set of SL crawling data described in Section II. However, to prevent influence from unreliable data, our experiments were performed with the data of the users who visited more than 25 areas. We show the details of processed SL data in Table II. This data set's sparseness is 97.64% and is close to the sparseness of CLiMF's evaluation datasets, such as Epinions[2] whose properties are also shown in Table II.

TABLE II. PRE-PROCESSED SECOND LIFE AND EPINIONS DATASETS

Dataset	Second Life	Epinions
#users	277	4718
#areas (items)	1402	49288
#non-zeros	9157	346035
Sparseness	97.64%	99.85%
Avg. visiting areas per user	33.06	73.34

B. Experimental Protocol and Evaluation Metrics

We carried out the same experimental protocol that was used for CLiMF. First, we divided the dataset into the training set and the test set under four situations: Given 5, 10, 15, and 20. For example, "Given 5" is the situation in which for each user we randomly chose 5 visited areas to form the training set, and used the remaining visited areas to

[2] http://www.trustlet.org/wiki/Downloaded_Epinions_dataset

form the test set. In our experiments, we used the training set to make the prediction model for each user, and the performance of the model was evaluated using the test set. We repeated evaluation 10 times for each situation of each pair of training and test sets, and the performances reported were averaged across 10 runs.

In the case of ranking recommendation, there is an idea of Less-is-More that we should provide users with only few valuable items. Thus, we evaluated the methods for only top-5 items in the recommendation list on the basis of this concept. To evaluate each method, we used 3 typical evaluation metrics: Top-5 Precision (P@5), 1-call at Top-5 (1-call@5), and Mean Reciprocal Rank (MRR). A brief explanation of each metric is as follows. P@5 is the average ratio of the number of actual relevant items in the top-5 recommended items (top-5 list). 1-call@5 is the average of the value that is 1 when there is at least one actual relevant item in the top-5 list. Thereby, the value of 1-call@5 is larger than or equal to that of P@5 for a given method. MRR is the average of the multiplicative inverse of the highest rank among the actual relevant items shown in the top-5 list, with such an inverse being zero if there is no relevant item in the top-5 list. For these evaluation metrics the higher value indicates a better performance.

V. RESULTS AND DISCUSSIONS

We show the results of our experiments in Table III, IV, V, and VI, where the best performance for each metric is in bold. These tables show that the CF methods outperform the baseline method PopRec in most experimental conditions. Table III, IV, V, and VI show the results due to varying the number of training data. In the general recommendation domain, there is a tendency that the CF's performance increases as the number of training data increases. This trend is also confirmed in our recommendation experiments in virtual space environment.

From the point of view for each evaluation metrics, achievement of high values of P@5 indicates the high quality of the entire recommendation list. Achievement of high values of 1-call@5 indicates that CF has succeeded in inclusion of preferred areas in the small-size recommendation list. As a result, the goal of Less-is-More, mentioned earlier, is met. Achievement of high values of MRR shows that CF could place preferred items at the top of the recommendation list. The results have similar trends to those in other recommendation areas [6] and show that CF can be applied to area recommendation in virtual worlds in addition to flat web contents. In addition, unlike the content-based approach adopted by Eno et al. [1], we could carry out recommendation even without utilizing the feature information on the areas or users. Since SL data has high sparseness, BPR-MF, which is based on the assumption that users have higher preference to relevant items, does not perform well, compared to CLiMF, due to lack of such items during training.

TABLE III. PERFORMANCE COMPARISON IN GIVEN 5

Method	P@5	1-call@5	MRR
PopRec	0.217	0.589	0.280
BPR-MF	0.152	0.436	0.213
CLiMF	**0.231**	**0.611**	**0.292**

TABLE IV. PERFORMANCE COMPARISON IN GIVEN 10

Method	P@5	1-call@5	MRR
PopRec	0.187	0.574	0.276
BPR-MF	0.193	0.478	0.228
CLiMF	**0.209**	**0.600**	**0.286**

TABLE V. PERFORMANCE COMPARISON IN GIVEN 15

Method	P@5	1-call@5	MRR
PopRec	0.146	0.478	0.233
BPR-MF	**0.179**	0.442	0.214
CLiMF	0.172	**0.526**	**0.255**

TABLE VI. PERFORMANCE COMPARISON IN GIVEN 20

Method	P@5	1-call@5	MRR
PopRec	0.103	0.377	0.189
BPR-MF	**0.167**	0.396	0.189
CLiMF	0.129	**0.430**	**0.218**

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we applied two state-of-the-art CF methods, BPR-MF and CLiMF, to data collected from the virtual world SL. Based on the experimental results, we could verify that CF methods are also applicable to the area recommendation problem in virtual worlds. In particular, CLiMF is more promising than BPR for this problem.

The data collected from SL was still smaller than those data used in existing recommender studies. In the future, therefore, we plan to collect more data and conduct experiments with them.

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