Ancient Japanese Painting Recommendation for Non-Japanese Novices

Jiayun WANG † Kyoji KAWAGOE ‡

† Faculty of Information Science and Engineering

〒525-0058, 1-1-1 Nojihigashi, Kusatsu-shi, Shiga Japan

E-mail: † gr0278vx@ed.ritsumei.ac.jp, ‡ kawagoe@is.ritsumei.ac.jp

Abstract In this research, we develop a recommender system based on Ritsumeikan Art Research Center (ARC) database, which stores a large amount of the digital version of ancient Japanese paintings (like Ukiyo-e). This database is often used by experts in related areas, but rarely used by novices, especially foreigners. Since the precious ancient Japanese paintings are also popular overseas, we are trying to build a recommender system that can be used easily for foreigners. This system can avoid the difficulty of searching items with keywords, which are only known by experts who understand Japanese. Therefore, even a new user can obtain his/her interested paintings. When a user comes to this system, he/she selects his/her interests among some displayed prints at the beginning. Then, with the use of recommender system, the system can find the Top-N interesting images to the user. At this time, we conduct a recommender system on the digital archive of ancient Japanese paintings for non-Japanese users. We are also looking forward to applying this system to other digital archives in the future. This can help an individual getting access to the global knowledge.

Keyword Japanese ancient painting, Recommender system, Digital archive

1. Introduction

The purpose of this research is to develop a recommender system for recommending ancient Japanese paintings for non-Japanese novices. At this time, we use Ukiyo-e prints as the recommendation art contents. Ukiyo-e is a kind of traditional Japanese art that depicts the daily life, architecture, scenery, customs, drama, etc., of the 17th century Japan.

Many digital archives collect Ukiyo-e prints, as it is a kind of precious art and culture. Ritsumeikan art research center database (http://www.dh-jac.net/db/nishikie/, ARC) is one of them. This recommender system is also based on this digital archive.

Ukiyo-e database is a subset of ARC dataset. We use the information in and about Ukiyo-e database in this research.

Recommender systems have been used by many e-commerce websites (such as Amazon), social network applications (such as Facebook), social curation websites (such as Pinterest.com), etc., but they are rarely implemented in digital archives, to filter contents that users are interested in. There are mainly three types of recommender system technologies: collaborative filtering (CF), content-based, and knowledge-based methods.

Below are three often mentioned common problems. The memory-based recommendation algorithms are much more sensitive to these problems than the model-based. Memory-based recommendation algorithms use similarity measures to select users (or items) that are similar to the active user, while model-based recommendation algorithms first construct a model to represent the behavior of the users and, therefore, to predict their ratings.

· Sparsity of the rating matrix. In most recommender systems, each user rates only a small subset of the available items, so most of the cells in the rating matrix are empty. In such cases, finding similarities among different users or items is challenging.

· Cold-start. Related to the previous problem, this one deals with the difficulty in making recommendations for users recently introduced into the system. In such cases, the users have not rated enough items yet, so the recommender system is unable to guess their interests. Some systems overcome this problem by forcing the user first to rate a given set of items. However, these initial ratings could introduce biases into the system.

· Shilling. Recommender systems could suffer spam attacks, mainly from users interested in misleading the system to recommend a certain product.

This research mainly focuses on the sparse problem and the cold-start problem.

In this paper, we propose the framework of a recommendation method for non-Japanese user to obtain recommendations of ancient Japanese paintings. In this proposed method, RBM method for CF efficiently solves the cold-start problem. It is also expected that content-based methods can address the sparsity problem of the current dataset.

2. RBM for CF

Recently, many recommendations methods of neural networks are proposed. Restricted Boltzmann machine (RBM) for collaborative filtering (CF) is one of the simple and efficient solutions, for its excellent performance on handling very large datasets, and modeling tabular data, such as user's ratings of items. At this time, we demonstrate that, the RBM method can be successfully applied to the ARC dataset.

RBM is a kind of generative network that can learn features (or patterns) as probability distribution from inputs. RBMs have been used as generative models for learning labeled or unlabeled tabular data sets.

The training procedure of the proposed RBM method is shown in Figure 1. Inputs are view frequencies of each image per user. Each node in visible layer represents a view frequency value. The inputs will go forward to the hidden layer, where each node represents a latent feature, and backward to visible layer again, therefore generate the output. The forward and backward path is defined with the weights, biases, and in most case activation functions.

Using the construction of RBM, when inputs are the viewed times of Ukiyo-e images of an individual user, one node represents the viewed times of one image; i.e. if the input data is the view history of user_1, and the value of node v_1 is 2, then user_1 has viewed the first image twice. This model makes predictions of inexplicit information. We normalized all the viewed times within one and five, integrator, to adapt the characteristics of RBM, that K-nary input data obtain better prediction results.

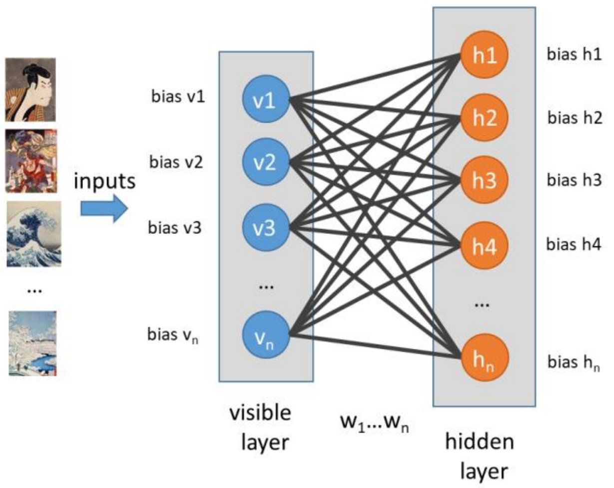

Figure 1: Structure of RBM in this system

We train and evaluate the RBM model on the user log access data. The original log access data consists of 43,126 records, indicating which users view which image at what time. We preprocess this original data to a format to show how many times one user viewed one item.

Figure 2 show the data distribution of three kinds of datasets: paintings database, books database, and pamphlets database.

We train and evaluate the RBM model on the user log access data. The original log access data consists of 28,191 records, indicating which users view which image at what time. We preprocess this original data to a format to show how many times one user viewed one item.

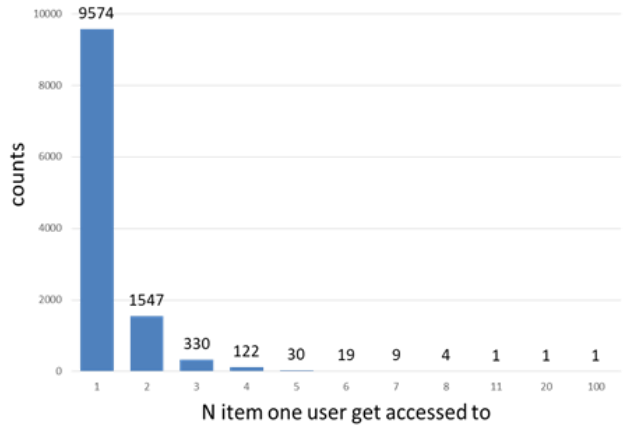

Figure 3: Data distribution of Ukiyo-e database.

To evaluate this algorithm, we use the mean absolute error (MAE) and the root mean square error (RMSE) to measure the difference between the real ratings and ratings predicted by this model on test data.

Figure 3: MAE and RMSE of prediction on Ukiyo-e.

We divided the dataset into training data and test data proportionally. MAE and MASE decrease when training data increase on the model and data.

3. CARC Method

3.1 Structure of CARC

CARC stands for content-based filtering after RBM for collaborative filtering. In this method, we use RBM for CF to make the prediction.

The structure of this method is shown in Figure 3.

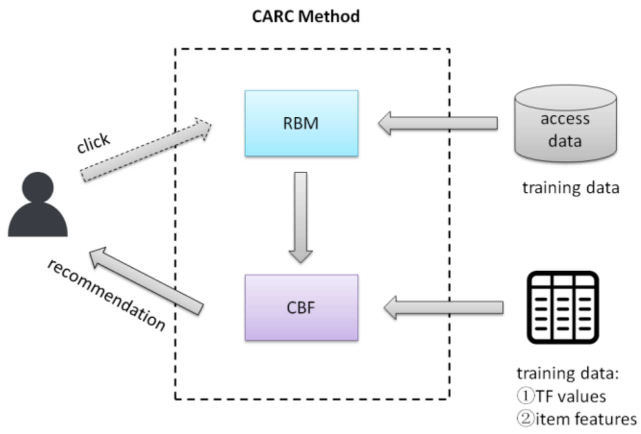

Figure 3: Structure of CARC

When a user comes to the recommender system, the restricted Boltzmann machine (RBM) method can initiate a recommendation list that adapts the current user's interests. And then, content-based filtering (CBF) method can make more accurate recommendation by recommending similar items.

In the case that a new user comes to the system at the first time, RBM can initiate a recommendation list for general user, and then the list will be optimized by CBF. Therefore addresses the cold-start problem. After interactions between the system and the new user, the history view of this user changes, thus the recommendation list changes. In this case, clicking on interested items on initial system is not necessary.

As written in the last section, RBM is trained by the access data of Ukiyo-e database. CBF uses TF values or item features in this method framework.

3.2 CARC-basic

This section talks about datasets of the CARC-basic method.

The access data of Ukiyo-e database is shown in Table 1.

user_id	item_id	view _frequency
1	1	1
1	3	2
…	…	…
8926	6855	1

Table 1: Training data of RBM.

Only viewed records exist in the data. "0"s will be populated in training data where a certain user didn't view a certain item before.

The recommendation of RBM can be regarded as a function below:

$$Recommendation = RBM(view\_frequency)$$

In this formula, "Recommendation" is a list of items. "View_frequency" represents the view times of one item per user.

3.3 CARC-TF

CARC-TF stands for c content-based filtering after RBM for collaborative filtering using term frequency.

In this case, term frequency is the sum of all the viewed times of a certain item.

item_id	frequency
1	28
2	6
…	…
6907	4

Table 2: Data of term frequency.

Content-based filtering uses this matrix to compute the similarity between every pair of items, creating an item-item matrix like shown below.

$$\begin{array}{cc} & \text{item} \\ \text{item} & \begin{bmatrix} 1 & & \dots & & & \dots \\ \dots & & & & & \\ 0.3 & \dots & 1 & \dots & 0.5 & \dots \\ \dots & & & & & \\ \dots & & \dots & & & 1 \end{bmatrix} \end{array}$$

Figure 4: Item-item matrix of content-based filtering using TF

This matrix will be multiplied by a vector of recommendation list, which is generated in RBM collaborative filtering for each user. The product of them is the new prediction.

3.4 CARC-W

CARC-W stands for content-based filtering after RBM for collaborative filtering using weights. Weights are the weighted item feature vectors.

In this algorithm, similarity between items is computed by a vector indicates the feature of items, multiplied by view frequency.

The original item feature vector of one item is like below:

$$Feature\_vector = \{0,0,0 \dots 1 \dots 1 \dots 0\}$$

Each value in this vector represents for a weight on a certain feature.

Then this vector is multiplied by value of view frequency; i.e. if this item is viewed by users for 5 times, the vector will be like this:

$$Feature\_vector = \{0,0,0 \dots 5 \dots 5 \dots 0\}$$

Finally, by calculating the similarities of every pair of items, multiplying the recommendation list, like what is done in CARC-TF method; the new recommendation list will be generated.

4. RELATED WORKS

The studies about digital archives and its recommendation methods are related to our research.

Avancini et al. proposed a paper that talks about adding recommender system in digital archives or digital libraries [3]. It highly recommends that digital archives can also be considered as collaborative meeting place of users, as well as a place that users can obtain their interested items and make the social network.

Manouselis, Nikos, et al. proposed a paper that provide an introduction to recommender systems for Technology enhanced learning (TEL) settings [4]. TEL is aims to design, develop and test sociotechnical innovations that will support individuals and organizations. They also highlight
the particularities of the recommender system by comparing it to recommender systems for other application domains.

5. CONCLUSION

We implement a recommender system on ARC database, and prove that RBM method obtains relatively good results in current researches. This system enables Non-Japanese novice users get access to ancient Japanese artworks like Ukiyo-e.

In this paper, we propose a method to consider this issue further more. That is to increase the prediction precision and to recommend items with variability, making all of the recommendations are based on the interests of those novice users.

The Non-Japanese novice users are easier to get access to the images stores in this database, as well as become more willing to learn these precious cultures

In the future, we are going to evaluate the two content-based filtering methods. See what the best plan for this issue is. We look forward to applying the system to digital archives and virtual museums for a more convenient and interest-based access.

REFERENCES

[1] G. Adomavicius and A. Tuzhilin. 2005. Towards the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. In IEEE Transactions on Knowledge and Data Engineering (June 2005), pp. 734 - 749.

[2] Fidel Cacheda and Víctor Carneiro, Diego Fernández, and Vreixo Formoso. 2011. Comparison of collaborative filtering algorithms: Limitations of current techniques and proposals for scalable, high-performance recommender systems. In ACM Transactions on the Web (Feb. 2011).

[3] Avancini, Henri, and Umberto Straccia. "User recommendation for collaborative and personalised digital archives." International Journal of Web Based Communities 1.2 (2005), pp, 163-175.

[4] Manouselis, Nikos, et al. "Recommender systems in technology enhanced learning." Recommender systems handbook (2011), pp, 387-415.

[5] Richard Socher, Brody Huval, Bharath Bhat, Christopher D. Manning and Andrew Y. Ng. 2012. Convolutional-recursive deep learning for 3D object classification. In NIPS'12 Proceedings of the 25th International Conference on Neural Information Processing Systems (Dec. 2012), pp, 656-664.

[6] Xavier Glorot, Antoine Bordes and Yoshua Bengio. 2011. Domain Adaptation for Large-Scale Sentiment Classification: A Deep Learning Approach. In Proceedings of the 28th International Conference on Machine Learning (ICML-11) (2011), pp, 513-520.

[7] Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton. 2012. ImageNet Classification with Deep Convolutional Neural Networks. In Advances in Neural Information Processing Systems 25 (2012).

[8] Hao Wang, Naiyan Wang and Dit-Yan Yeung. 2015. Collaborative Deep Learning for Recommender Systems. In KDD '15 Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Aug 2015), pp, 1235-1244.