Recommendation for Decision Support on Cloud Data Center based on Operation and Maintenance Knowledge Graph

Hongbo Lu[1], Yiyou Yuan[1,*], Dequan Gao[2], Ziyan Zhao[2], Fenggang Lai[2], Chao Ma[3], Hao Xu[3], Yin Liu[3]

[1.] *State Grid Information and Telecommunication Group Co., Ltd, China*
[2.] *State Grid Information and Telecommunication Branch, China*
[3.] *State Grid Shandong Electronic Power Company, China*
The corresponding author's e-mail address: yuanyiyou@qq.com

Abstract.
With the rapid development of Cloud Data Center, the recommendation systems that provide valuable suggestions for the users to address the problem of information over-loaded have provoked a vast amount of attention and research from multiple disciplines. In recent decades, both the matrix factorization (MF) and deep learning methods have achieved fairly good performance for the recommendation. However, in the field of Operation And Maintenance (OAM) cloud data center, due to the intricate nature of the faults data in multi-level and diversified OAM scenarios, the sparsity of data may lead to significant degradation of recommendation performance, which pose huge challenges to the existing recommendation methods. To address these problems, in this paper, we propose a recommendation method for Decision Support on Cloud Data Center based on the operation and maintenance Knowledge Graph. Specifically, fault-based and solution-based representations are learned for Collaborative Filtering (CF), which has been proven to be one of the most commonly applied and successful recommendation approaches. Meanwhile, faults' attributions are combined into the representations by OAM Knowledge Graph for alleviating the sparsity problem. Experimental results demonstrated the effectiveness of our proposed method in the OAM cloud data center for decision support.

Keywords: *Recommendation, operation and maintenance Knowledge Graph, decision support, Cloud Data Center*

1. Introduction

In the period of big data, recommendation system has played an increasingly crucial role in many online services, such as electronic commerce [1], personalized advertising [2], and social networks [3]. Last decades have witnessed a vast amount of interest and research in the recommendation systems, the main idea behind the recommendation is to use user-item interaction information for analyzing user preferences for items [4]. With the rapid development of cloud data center, the recommendation systems can provide valuable Operation And Maintenance (OAM) suggestions for the users to address the problem of information over-loaded [5].

In recent decades, both the matrix factorization (MF) and deep learning methods have achieved fairly good results and applied widely in recommendation systems. The matrix factorization recommendation methods aim to decompose the interaction between users and items into user- and item-specific representations for better prediction [6]. However, the inherent limitations in feature representation learning over these MF methods may be greatly detrimental to the recommendation performance. Recently, due to the powerful ability in feature representation learning, advances in deep neural networks have far-ranging consequences in practical recommendation applications. For example, He et al. [7] proposed a neural network-based method, which focused on implicit feedback of collaborative filtering

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and introduced a multilayer perceptron for user-item interaction functions learning.

Though deep learning based methods have achieved satisfied results in conventional recommendation scenarios, there are still some problems that prevent the further development of these methods in the recommendation for decision support on the cloud data center. Firstly, in the field of the cloud data center, the operation and maintenance data is intricate in multi-level and diversified scenarios. The relations between different entities are difficult to explore, and the features of entities and relations are hard to express. Secondly, the sparsity of OAM data inevitably caused significant degradation of recommendation performance. These methods pose huge challenges to the existing recommendation methods.

To address these problems, in this paper, we propose a recommendation method for Decision Support on Cloud Data Center based on the operation and maintenance Knowledge Graph (DC-CDC for short), which can recommend accurate OAM fault handling strategies for users in the cloud data center. More specifically, fault-based and solution-based representations are learned respectively with a semi-autoencoder model, which can capture the different characteristics of faults and solutions for the recommendation. Meanwhile, the faults' attributions (the attributions about OAM faults) are combined into the representations learning by the OAM Knowledge Graph, which can alleviate the sparsity problem of OAM data. Experimental results demonstrated the effectiveness of our proposed method in the OAM cloud data center for decision support.

The main contributions can be summarized as the following:

- A recommendation method for the cloud data center is proposed, which can address the method of OAM decision support;
- The OAM Knowledge Graph is utilized to extract better feature representations for improving recommendation performance;
- Experimental results confirm the effectiveness of the proposed method in the recommendation.

2. Related Work

The recommendation system aims to leverage interaction information for analyzing user preferences for items. Based on how the feature representations are learned, existing methods can roughly be categorized into the following two classes: matrix factorization and deep neural network methods [8].

The matrix factorization methods decompose the interaction between users and items into user- and item-specific representations, which have been applied widely in a broader set of scenarios. For example, Non-negative Matrix Factorization (NMF) model [9] can be used to factorize the rating matrix into user and item profiles for the recommendation. Along this line, Probabilistic Matrix Factorization (PMF) [10] and Bayesian Probabilistic Matrix Factorization (BPMF) [11] scale linearly with the number of observations and achieve better results in the recommendation. SVD++ [12] further extends the model to take advantage of users' explicit and implicit feedback.

Recently, deep neural networks have emerged as a powerful instrument for a personalized recommendation. For example, Wang et al. proposed a collaborative recurrent autoencoder [13], which models the generation of content sequences in the CF setting. Zhuang et al. proposed a representation learning framework based on the dual-autoencoder model for the recommendation, the deviations of training data are minimized by the reconstructed features of users and items.

3. Methodology

In the scenario of decision support on cloud data center, the recommendation aims to predict the solution of fault based on the interaction matrix and auxiliary information. Given the interaction matrix $R \in \Re^{m\times n}$, where m and n represents the number of faults and solutions respectively, $Q \in \Re^{m\times n}$ is the corresponding indicator matrix, where $Q_{ij} = 0$ if $R_{ij} = 0$, and $Q_{ij} = 1$ if $R_{ij} \neq 0$.

$$J_{solutions} = \left\| Q^S \bullet (R^{S\prime} - R^S) \right\|^2 \quad (1)$$

where $R^{S\prime} = \mathrm{g}(W_2^S f(W_1^S R^S + b_1^S) + b_2^S)$,where R^S and Q^S are the interaction matrix and indicator matrix of solutions, W_1^S , W_2^S , b_1^S , and b_2^S are the weight matrices and bias vectors of encoder and decoder layer respectively.

Meanwhile, a semi-autoencoder model is introduced to combine the faults' attributions (the attributions about OAM faults) by OAM Knowledge Graph. R^F and A^F are denoted as the faults-based matrix and auxiliary information respectively, we input the concatenation of R^F and A^F as $con\left(R^F, A^F\right)$ to the semi-autoencoder model, then the encode and decode layer of the semi-autoencoder model can be shown as (2) and (3) as follows:

$$\xi^F = f\left(W_1^F con\left(R^F, A^F\right) + b_1^F\right) \quad (2)$$

$$R^{F\prime} = g\left(W_2^F \xi^F + b_2^F\right) \quad (3)$$

where $W_1^F \in \Re^{(m+y)\times h}$ and $b_1^F \in \Re^h$ are the weight matrix and bias vector of encoder layer in the semi-autoencoder model, y represents the number of attribute features, h represents the dimensions of hidden layer. $W_2^F \in \Re^{h\times m}$ and $b_2^F \in \Re^m$ are the weight matrix and bias vector of decode layer in the semi-autoencoder model, f and g are the nonlinear activation function, the sigmoid and identity functions are applied in the proposed method. Due to the output of the semi-autoencoder model being the partial reconstructions of input, the objective function can be formulated as (4):

$$J_{faults} = \left\| (R^{F\prime} - R^F) \right\|^2 \quad (4)$$

Finally, after the features of faults and solutions are learned with autoencoder and semi-autoencoder models, the predicated matrix can be calculated as (5):

$$\hat{R} = [\left(\xi^F\right)^T \bullet \xi^S] \quad (5)$$

4. Experiments

4.1. Dataset

To verify the effectiveness of our proposed method, we conduct experiments on the operation and maintenance dataset in the cloud data center of the Electric-Power Industry. In the experiments, we conduct a snapshot of the operation and maintenance dataset, which contains 672 solutions and 3952 faults with 100000 values. The dataset also contains information about the faults (the attributions about OAM faults) like faults type, occurrence time, category, and so on.

4.2. Compared methods and evaluation metrics

4.2.1. Compared methods.

- NMF (Non-negative matrix factorization) [9], a classical MF method, which factorizes the rating matrix into user and item profiles for the recommendation;
- PMF (Probabilistic Matrix Factorization) [10], which scale linearly with the number of observations and achieves better results in the recommendation.

4.2.2. Evaluation metrics.

In the experiments, the Root Mean Square Error (RMSE) is introduced to evaluate the recommendation effectiveness, which is defined as (6). It is worth mentioning that the smaller values of RMSE indicate the better performance of the methods.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{r_{u,i} \in \mathrm{TestSet}} \left(r_{f,s} - \hat{r}_{f,s}\right)^2}{|\mathrm{TestSet}|}} \quad (6)$$

where $r_{f,s}$ represents the whole interaction matrix, and $\hat{r}_{f,s}$ represents the prediction matrix.

4.3. Experimental Results

We show the experimental results in Table 1. Overall, our proposed method outperforms compared methods, which demonstrate the effectiveness of incorporating auxiliary information from the OAM Knowledge Graph.

Table 1 The RMSE results of all methods

Methods	The proportion of training data	
	70%	80%
NMF	1.156	1.112
PMF	1.096	1.084
Our method	**0.973**	**0.952**

4.4. Decision support

Besides the recommendation results, we conduct the decision support with similarity calculation among different solutions. With the results of faults-based and solutions-based feature representations learning by (1) and (4), the decision support can be conducted based on the similarity between solutions-based features, the results can be shown in Table 2.

Table 2 The accuracy results for decision support of all methods

Methods	The proportion of training data	
	70%	80%
NMF	0.64	0.67
PMF	0.69	0.71
Our method	0.82	0.87

5. Conclusion

In this paper, we propose a recommendation method for Decision Support on Cloud Data Center based on the operation and maintenance Knowledge Graph. The fault-based and solution-based representations are learned for Collaborative Filtering. Furthermore, faults' attributions are combined into the representations by OAM Knowledge Graph for alleviating the sparsity problem. Experimental results have demonstrated the effectiveness of our proposed method for recommendation and decision support.

In the future, we try to extend our work in two directions: the first is to incorporate more auxiliary information for feature representation learning in recommendation; the second is to construct a larger OAM Knowledge Graph for decision support in Cloud Data Center.

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