CHAPTER 1

INTRODUCTION

1.1 Rationale

The amount of information available often makes it difficult for individuals or groups to process and manage it effectively [1]. Recommender systems come as a solution to this problem by helping users find relevant and useful information among the mass of data [1]. Recommender systems provide preferences by collecting information such as ratings, reviews, or opinions from previous users to be processed and given to users in the form of preferences [2].

To date, many recommender systems have been developed for personal user cases [3–5]. However, in daily life, there is often interaction in the form of groups, such as listening to music with friends, watching movies with family, planning vacations with colleagues, etc. [6]. Therefore, group recommender systems have the same level of importance to be completed in addition to personal recommender systems [6]. Group recommender systems can be built with two methods, i.e., aggregate model and aggregate prediction [7]. Aggregate model is a method that combines user profiles from each group member into a group profile before making recommendations [7]. Meanwhile, aggregate prediction is a method that combines recommendation results for each user profile from a group [7]. Both methods have the same challenges, one of which is the problem of data sparsity [8].

Data sparsity is a condition where many items have not been rated by users [9]. In practice, user-item interactions are very sparse because users usually only rate a small percentage of available items among a large number of items [10]. As a result, this sparsity of data in the rating matrix is a challenge in group recommender systems [8]. For example, data that are often used in recommendation systems have huge sparsity levels such as Movielens 100k with a sparsity level of 94%, Movielens 1M with a sparsity level of 96%, and Netflix dataset with a sparsity level of 98.5% [11, 12].

In previous research, the matrix factorization (MF) model which is a paradigm of collaborative filtering (CF) is widely used to build group recommender systems [6, 13–15]. The MF model has shown good performance, but this model has shortcomings in overcoming data sparsity which can reduce the accuracy of prediction [16–18]. MF is proven to be able to solve the sparsity problem, however, MF does not completely solve this problem, especially if the data is too sparse [10, 18].

Lately, deep learning has received significant attention in the development of machine learning, one of which is in the development of recommender systems [19]. Deep learning is applied in recommender systems to provide alternative solutions to accuracy, cold-start, and data sparsity problems that exist in previous recommender systems [20]. Autoencoder (AE) is among the deep learning techniques employed in recommender systems to overcome scalability and data sparsity issue [20, 21]. Sparse AE is a part of AE where there is an addition of sparse regularization to the AE model [22]. In previous research, sparse AE has been used in the case of personal recommender systems to overcome sparsity problems [23]. This model shows better performance compared to several base models tested using datasets with different levels of sparsity [23].

Therefore, we propose an approach by utilizing sparse AE to address the sparsity issue. In this study, we apply the sparse AE model to a group recommender system. Indeed, there have been many studies used in group recommender systems to overcome the sparsity problem, such as MF, MF has indeed been proven to be able to overcome this sparsity problem, but MF cannot fully overcome this problem. MF has disadvantages especially when the data is too sparse, where in real conditions users give only a few ratings from the many items available, so the data becomes very sparse. Sparse AE as one of the deep learning models, which has the ability to learn complex latent representations and handle data sparsity more effectively. Sparse AE is expected to improve the performance of the group recommender system, even under the conditions of very sparse and complex data. We use several aggregation methods and various group formation size scenarios to build a group recommender system. The evaluation is done by comparing our proposed model with MF model with the same scenario. In the evaluation, we use root mean square error (RMSE) and mean absolute error (MAE).

1.2 Theoretical Framework

This section explains the theoretical framework that underlies the research of building a recommender system using sparse autoencoder.

1. Group recommender system: a group recommender system is a system that provides a recommendation of an item for a group.

2. Sparsity problem in group recommender system: in the group recommender system, the sparsity problem refers to the condition where the user-item data is mostly empty or unfilled.

3. Sparse autoencoder: the sparse autoencoder is a type of neural network that is used primarily for dimensionality reduction and feature coding. This model has the advantage of handling scalability and sparsity issues.

4. Aggregation strategy: aggregation method is a technique to combine the prediction results of users in one group to produce a group recommender system.

1.3 Conceptual Framework/Paradigm

In building a group recommender system, one of the problems that comes up is the problem of data sparsity, this is because the user-item data used is mostly empty. To handle the sparsity problem, we propose a sparse autoencoder. Sparse autoencoder is chosen because it has advantages in handling the sparsity problem [23]. We do an aggregation strategy from the prediction results to build a group recommender system.

1.4 Statement of the Problem

Sparsity is one of the problems in group recommendation systems [11]. Previous research, to deal with sparsity problems in group recommender systems, many were built using the MF model [6, 13–15]. The latest research tries to improve the group recommender system using slope one, but the MF model is still better for many cases, but the slope one model has the advantage of producing recommendations faster than matrix factorization [8]. From this, it is known that the MF model is still leading in building a group recommender system in terms of performance. However, the MF model still has shortcomings in handling sparsity problems [16–18]. From this we find a research gap to improve the performance of the group recommender system using a model that can handle sparsity problems better than the MF model.

1.5 Objective and Hypotheses

From that problem, we propose a sparse autoencoder model to build a group recommender system. We chose the sparse autoencoder model because it has advantages in handling scalability and sparsity problems [20, 23]. Sparse autoencoder is a part of autoencoder [23]. In previous research, the autoencoder model has been used to solve the sparsity problem in the case of a personal recommender system [10]. In that research, the autoencoder model outperformed the MF model. To build a group recommender system, there is a difference by adding an aggregation strategy so that the recommendations produced are in the form of groups [6]. This gives us confidence that the sparse autoencoder model can be applied to group recommender systems and provide better performance. Based on these facts, this research hypothesizes that the sparse autoencoder model can provide a better performing group recommender system.

1.6 Assumption

We assume that each group member has different preferences when selecting recommended items. In addition, we assume that the sparse autoencoder can handle the sparsity problem better than the MF model, which can improve the performance of the group recommendation system.

1.7 Scope and Delimitation

The main focus of this research is to improve the performance of the group recommender system using sparse autoencoder. Our group recommender system is not domain specific, therefore we use a common and most used dataset which is MovieLens dataset [11]. To measure performance, we compare the sparse autoencoder model with MF using MAE and RMSE evaluation metrics.

1.8 Significance of the Study

This research proposes a sparse autoencoder model to overcome the sparsity problem in group recommender systems. This is done because sparsity is one of the problems that exist in group recommender systems. The contribution of this research is to improve the performance of the group recommender system and give insight that handling sparsity better can improve the performance of the group recommender system.