



1. INTRODUCTION

With the ease of accessing music streaming services such as JOOX, Spotify, and Apple Music, the quantity of digital music in this era will continue to grow. With this rapid growth, the task of discovering new and suitable music for users can lead to decision fatigue, and a tendency to defer making choices when confronted with an overwhelming number of choices [1]. Recommender systems (RS) can help users overcome these problems by providing them with a set of music recommendations that suit their preferences [2]. Collaborative Filtering (CF) is among the used and successful paradigms for building an RS [3].

The main concept of the CF paradigm is to predict the ratings that users will give to each item based on the similarity between users and/or other items [3]. CF has two approaches: memory-based and model-based. Although frequently used, memory-based CF requires a lot of resources because the matrix needs to be loaded into main memory each time a recommendation is made [2]. Furthermore, issues such as synonymy, sparsity, and scalability [4] are limitations of this approach. In the model-based approach, the prediction process is based on a pre-built model using machine learning algorithms and data mining techniques [2], [5]. Although it requires time to build the model and train the data, the storage required is smaller, and it can address the issues of memory-based approaches, resulting in more accurate predictions [6].

Ratings used in this paradigm are divided into two types: explicit feedback and implicit feedback [4]. Explicit feedback is direct user input on an item, such as providing a rating, while implicit feedback is indirect, such as the number of plays, clicks, or transactions. Explicit ratings can also have implicit ratings, for example, when a user rates a news article, we can infer (implicitly) that the user likes the topic or the writer of that article [7]. Leveraging implicit feedback in recommender systems can increase user interaction compared to using explicit feedback [8]. One method that can be used to predict ratings is Matrix Factorization.

Matrix Factorization (MF) is a commonly used supervised learning approach that achieves high accuracy in addressing sparsity issues in the data used in RS [9]. Singular Value Decomposition (SVD) is one of the MF algorithms that works by reducing the dimensionality of the matrix [10]. Singular Value Decomposition++ (SVD++) is an extension of the SVD algorithm [5] and can utilize implicit feedback as input, which better reflects user preferences [11].

Tian et al. in 2019 [12] used Logistic Regression (LR), XGBoost, and a combination of both (LX) to build a music recommender system using the MSD dataset [13]. Before making predictions, user profiles are constructed based on their music playback history. The prediction results are evaluated using error metrics and Area Under Curve (AUC). LR yielded an error value of 0.3062 and AUC of 0.7268, XGBoost had an error of 0.2723 and AUC of 0.7663, and LX achieved an error of 0.2376 and AUC of 0.8087. Based on these results, it can be concluded that LX outperformed LR and XGBoost models.

Dong et al. conducted research in 2020 [14], the Last.fm dataset from MSD [13] was used to build a music recommender system based on Fusion Deep Learning model. The input features for the model included audio files converted into spectrogram images and lyrics rewritten without losing their emotional expressions. The model used feature extractors based on Convolutional Neural Network (CNN) for spectrogram and emotion extraction from lyrics, along with an LR-based recommendation prediction model. The prediction results were evaluated using accuracy metrics, and the recommendation accuracy was reported as 90.2.

In 2018, Liu et al. [15] conducted research using a book lending dataset over a four-year period, consisting of user ID, book ID, loan days, and timestamp from the Aleph library system in a school. The loan days feature, an implicit feature, was used as input for the recommender system built using the SVD++ algorithm. Testing was performed with different numbers of latent factors (20, 50, 100, 150, 200, and 500), and the evaluation using RMSE showed that the model with 100 latent factors had the best accuracy with an RMSE value of 0.977.

Biswal et al. conducted research in 2020 [2] to build a music recommender system using the MSD [13] Subset from The Echo Nest, utilizing the Restricted Boltzmann Machine (RBM) and the CF engine by Apache with implicit feedback in the form of user music play counts as input. The dataset was divided into 80% training and 20% testing sets before evaluation. Confidence scores, ranging from 0 to 1, were used as ratings in the prediction phase, calculated based on the number of music played. Confidence scores represent the certainty of recommending an item to a user. The evaluation results using the Normalized Root Mean Squared Error (NRMSE) metric showed that RBM had better accuracy than the CF engine by Apache with value of 0.0075 and 0.0200 respectively.

Pujahari et al. in 2020 [16] conducted research to compare the performance of model-based CF methods, utilizing MovieLens dataset. One of the methods used was matrix factorization, with two algorithms employed: SVD and SVD++. The performance of the built models was measured using Normalized Discounted Cumulative Gain (NDCG) with a parameter $D = 60$, resulting in values of 0.4154 for SVD and 0.4441 for SVD++. From these results, it can be concluded that SVD++ outperformed SVD.

Research by Chen et al. in 2020 [17] built a recommender system using the MSD Last.fm dataset [13] with a hybrid approach consisting of item popularity-based method and SVD, utilizing the music play count feature.



Before being used for prediction, these play counts were transformed into LScore ranging from 1 to 5. The main concept of LScore was to consider the ranking of music. The prediction results were evaluated using precision metrics, and the hybrid model that was built was compared with the results from the SVD model and item popularity. The hybrid model showed better prediction results compared to the other two models, with a precision value of 0.509, compared to 0.438 for SVD and 0.407 for item popularity in the top 4 music recommendations.

In this research, we will be developing a recommender system and performing an in-depth analysis of the recommender system model's performance built with SVD++ and Million Song Dataset The Echo Nest Taste Profile Subset dataset. In the development process, we utilize implicit feedback in the form of the number of music played as the input for the SVD++ model. Additionally, to differentiate with previous research we incorporated k-fold cross-validation with combination of RMSE and NDCG evaluation metric to evaluate the model. Through this research, we aim to offer valuable insights and establish a foundational benchmark than can be utilized for future research comparisons.