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Enhancing Recommender Systems with NLP-based Biased Singular Value Decomposition

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Abstract. **This research introduces a novel Natural Language Processing (NLP) based Biased Singular Value Decomposition (SVD) Recommender System that addresses the limitations of existing methods while maintaining high-quality recommendations. By incorporating advanced NLP techniques and Biased SVD, this paper introduces a controlled bias that accounts for both user and item biases, effectively enhancing the performance of the recommender system while maintaining a certain degree of fairness and transparency. In addition, neural network-driven sequential models are incorporated to enhance the recommender system's overall performance. These approaches contribute to the development of efficient, fair, and transparent recommender systems that cater to the diverse needs and preferences of users in the digital era.**

Keywords: Recommender System, NLP, Biased-SVD, Sequential Model.

I. Introduction

In recent years, the rapid growth of digital content and the increasing reliance on personalized services have sparked significant interest in the development of sophisticated recommender systems. These systems aim to provide accurate and relevant recommendations to users, thereby enhancing their overall experience and engagement. However, existing methods face certain limitations, such as computational complexity and challenges related to bias and fairness in the recommendation process.

To address these limitations, this paper introduces a novel approach: the Natural Language Processing (NLP) based Biased Singular Value Decomposition (SVD) Recommender System. The primary motivation behind this approach is to leverage advanced NLP techniques to analyze and extract meaningful information from textual data, enabling the recommender system to uncover complex patterns and relationships within the content.

By incorporating Biased SVD, this paper introduces a controlled bias that takes into account both user and item biases. This inclusion enhances the performance of the recommender system while maintaining a certain degree of fairness and transparency. By doing so, the proposed approach aims to provide high-quality recommendations while addressing the challenges of bias and fairness that are prevalent in many existing recommendation methods.

The significance of this work lies in its potential to contribute to the ongoing discourse on the development of efficient, fair, and transparent recommender systems that cater to the diverse needs and preferences of users in the digital era. Through a thorough analysis of the NLP-Based Biased SVD Recommender System, this paper aims to shed light on the advancements in recommendation techniques and foster discussions on creating systems that not only excel in accuracy but also uphold principles of fairness and transparency.

II. Related Work

In the context of recommender systems, SVD is a popular matrix factorization method to capture latent factors like item characteristics and user preference from a user-item interaction matrix and then predict a user's rating. However, this normal SVD technique does not consider intrinsic biases, including that certain users rate movies more critically or generously. Biased SVD, a widely used approach in the development of recommender systems, solves this problem as it can efficiently handle the issue of data sparsity by modeling the inherent biases in the user-item interactions [2,3]. By taking both global and individual preferences into account, Biased SVD significantly improves the accuracy of recommendations. This technique decomposes the user-item interaction matrix into lower-dimensional latent factor matrices, which capture the underlying patterns in the data while incorporating user and item biases that may arise from factors such as popularity or personal preferences [4]. The combination of latent factors and biases makes Biased SVD a powerful method for generating personalized recommendations, as demonstrated by its successful application in various real-world scenarios, such as the Netflix Prize competition [5].

Simon Funk's pioneering work on SVD in the context of recommender systems has been widely acknowledged for its contributions to collaborative filtering [6]. The "Funk-SVD" algorithm, developed during the Net-flix Prize competition, offers significant advantages over traditional SVD, including improved scalability and computational efficiency. However, some drawbacks of Funk's approach have been noted, such as its susceptibility to overfitting, and its inability to handle cold-start problems, where the algorithm struggles with new users or items with limited data [7].

Funk's work has inspired numerous subsequent research efforts, such as the development of SVD++ by Koren [4], which extends the traditional SVD model by incorporating implicit feedback, and hybrid models that merge matrix factorization methods with content-based approaches [8, 9]. Despite some limitations, Simon Funk's work on SVD has had a substantial impact on the field of recommender systems, providing the foundation for more advanced and sophisticated latent factor models.

Sequential models also play a crucial role in recommender systems by capturing temporal dependencies and providing personalized recommendations based on the user's historical behavior. These models take the order and sequence of user-item interactions into consideration, allowing for more accurate predictions and improved recommendation quality. One popular sequential model is the Recurrent Neural Network (RNN), which has been widely used in recommender systems. RNNs, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), can effectively capture sequential patterns and model the evolving preferences of users over time [10, 11]. They have been shown to outperform traditional collaborative filtering methods in scenarios where the order of interactions matters. Additionally, advanced sequential models such as the Transformer-based models have gained attention for their ability to handle long-range dependencies and capture complex sequential patterns [12]. These models have shown promising results in various recommendation tasks, including session-based recommendation and next-item prediction. Overall, sequential models offer valuable insights into user preferences and behavior, enabling personalized and context-aware recommendations in recommender systems [13, 14].

In this study, we investigate the integration of NLP techniques with Biased SVD in the context of recommender systems. Our experimental results demonstrate the effectiveness of this combined approach in enhancing the accuracy of recommendations. This novel methodology leverages the strengths of both NLP and Biased SVD, harnessing the power of textual information and addressing inherent biases in user-item interactions to create a more robust and personalized recommendation engine.

III. Dataset

We utilized the publicly available Amazon 5-core Movies and TV dataset from 2018. This dataset comprises 3,410,019 reviews, having been filtered to retain only the 5-core subset. The 5-core criterion ensures that each remaining user and item in the dataset has at least five reviews, allowing for more reliable and consistent analysis.

The dataset's structure is systematically organized and can be visualized in Figure 1. The figure provides a clear representation of the data schema, enabling a comprehensive understanding of the relationships between various entities, such as users, items, and reviews. This well-structured dataset serves as a solid foundation for our research and analysis, facilitating the development of effective recommendation models.

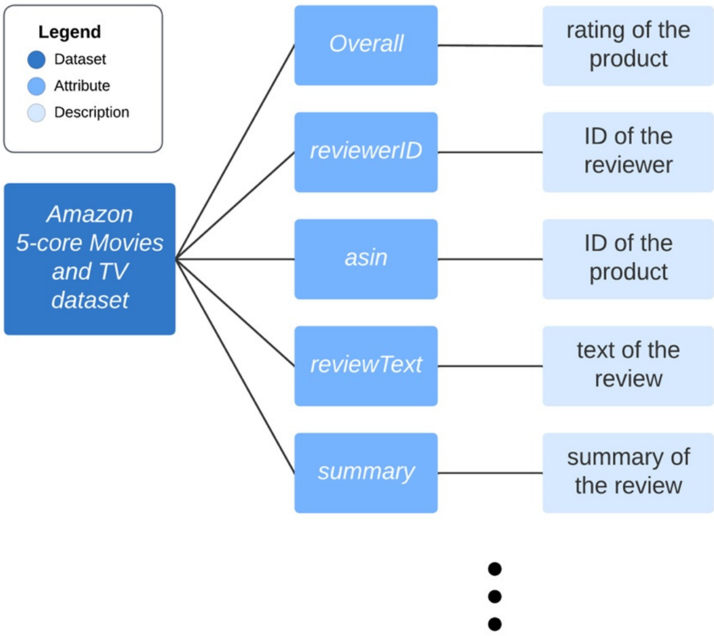

Figure 1. Amazon Movie and TV Dataset Schematic Graph

A standard data partitioning strategy is employed for training and evaluating our model. Specifically, we allocated 80% of the dataset for the training set, while the remaining 20% was further divided equally into a training-validation set and a separate testing set, each comprising 10% of the original dataset. In order to develop an accurate and practical model, we employed a leave-one-out [15] approach for partitioning the dataset into a training set, a validation set, and a testing set. Recognizing that the use of future transactions to predict past purchases would introduce look-ahead bias and lead to unrealistic performance estimates, we implemented a time-aware splitting strategy. To achieve this, we first sorted the data in ascending order based on transaction timestamps, ensuring that the model would adhere to real-world temporal constraints.

Subsequently, for each user within the dataset, the most recent transaction was allocated to the test set, the penultimate transaction to the validation set, and all remaining transactions to the training set. This process facilitated a rigorous and tempo-rally coherent evaluation of the model's performance.

Furthermore, in an effort to enhance the granularity of the user-item interaction analysis, we incorporated sentiment analysis of the associated review texts, whenever available. By extracting and analyzing the sentiment expressed in these reviews, we were able to predict user review ratings, which could then be combined with explicit user ratings for a more comprehensive understanding of the user-item interaction. This integration of both implicit and explicit feedback contributes to a more robust and well-rounded representation of user preferences, ultimately leading to more effective recommendations.

IV. Method

We propose two improvements to the baseline Simon Funk SVD model. The first improvement, called Biased SVD (ratings only), takes user and item biases into account by adding additional terms to the equation. Here is the formulation:

$$r_{ui} = \bar{r} + \omega_1(\mu_u - \bar{r}) + \omega_2(\mu_i - \bar{r}) + p_u \cdot q_i + b_u + b_i \tag{1}$$

The second improvement, called Biased SVD (ratings + sentiment), also considers review sentiments by incorporating them into the equation. The two enhancements are designed to enhance the accuracy of predicting the ratings in the user-item matrix blanks. The Flowchart for the model is shown in Figure 2. Here is the formulation:

$$\begin{aligned} r_{ui} = \bar{r} + \omega_1(\mu_u - \bar{r}) + \omega_2(\mu_{ui} - \bar{r}) + \omega_3(\mu_i - \bar{r}) \\ + \omega_4(\mu_{ni} - \bar{r}) + p_u \cdot q_i + b_u + b_i \end{aligned} \tag{2}$$

We consider a rating system where each user and item is represented by a vector r_{ui} that represents the calculated rating. The global mean rating is denoted as $\bar{r}$, while the mean rating of all transactions involving a user is represented by μ_u and the mean rating of each item is represented by μ_i. To capture review sentiment, we introduce the user mean rating considering sentiment generated by BERT as μ_{ni} and the item mean rating considering sentiment as μ_{ui}. We use trainable parameters $\omega_1, \omega_2, \omega_3, b_u, b_i$ that are estimated via Stochastic Gradient Descent to optimize our model. Additionally, we employ dimension reduction techniques to represent users and items as matrices with elements p_u and q_i, respectively.

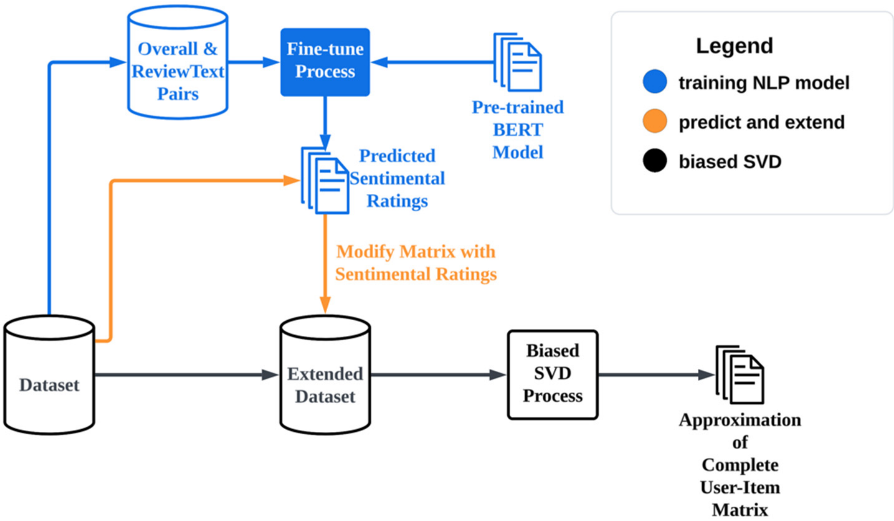

Figure 2. Flowchart of Enhanced Biased SVD Model of NLP Bias Mitigation

V. Experiments

A. *Bias-SVD Models*

The experiment utilized three SVD-based models, all trained for 100 epochs with Stochastic Gradient Descent as the optimizer, and RMSE as the loss function. To prevent overfitting, early stopping was implemented based on the validation loss. The performance of the models was evaluated using the MAE and RMSE metrics on the validation set.

Table 1. Test results for Bias-SVD Models

	RMSE	MAE
Simon-Funk	1.0896	0.8543
Bias (Rating)	1.0854	0.8427
Bias (Rating & NLP)	1.0891	0.8416

The results in TABLE 1. indicate that the base Simon Funk SVD model exhibited the poorest performance, with the longest convergence time and no early stopping triggered. In contrast, the biased model with ratings only, which includes bias terms for users and items, exhibited superior performance on the two evaluation metrics. It achieved convergence in approximately half the time compared to the baseline model, leading to the activation of early stopping. The SVD model considering both sentimental text and ratings, also led to early stopping and demonstrated faster convergence than the baseline Simon Funk SVD model, albeit not as rapid as the Ratings SVD model. Overall, the performance of the Ratings & NLP SVD model was between that of the base Simon Funk SVD and Ratings SVD models. These findings suggest that incorporating bias terms and review sentiments can enhance the predictive power of SVD-based models for recommendation systems.

B. Sequential Model

The experiment for sequential models uses NDCG@10 (Normalized Discounted Cumulative Gain for the top 10 recommendations) as the metric, which considers both the gain/rating and the ranking quality of the top-10 recommendation list. The higher NDCG@10 means the recommended items/movies have higher ratings and the top-10 recommendation list is more like the ideal ranking list sorted by the 10 movies' ratings. The test result in TABLE 2. demonstrates, among GRU4Rec, SLi-REC, and FPMC, FPMC emerges as the most promising algorithm for the Amazon 5-core Movies and TV dataset. The strength of FPMC lies in its ability to capture both collaborative and sequential patterns effectively. As the dataset likely contains user-item interactions as well as sequential dependencies, FPMC's combination of collaborative filtering and Markov chain modeling allows it to excel in this context. By leveraging collaborative filtering, FPMC can capture the collective preferences of users and the similarities between items. Simultaneously, the inclusion of Markov chain modeling enables FPMC to understand the sequential patterns and transitions within user interactions. This unique fusion empowers FPMC to generate recommendations that are not only personalized but also incorporate the temporal dynamics and order of user actions. Consequently, FPMC outperforms GRU4Rec and SLi-REC on Amazon 5-core Movies and TV dataset by delivering more accurate and relevant movie recommendations to users based on both their collaborative and sequential preferences.

Table 2. Test results for sequential model

	NDCG@10
GRU4Rec	0.0692
SLi-REC	0.0728
FPMC	0.0739

VI. Conclusions

This paper presents a novel Natural Language Processing (NLP) based Biased Singular Value Decomposition (SVD) Recommender System that addresses the limitations of existing methods while maintaining high-quality recommendations. By incorporating Biased SVD, this paper introduces a controlled bias that accounts for both user and item biases, effectively enhancing the performance of the recommender system while maintaining a certain degree of fairness and transparency. Among the sequential models tested, FPMC emerged as the most promising algorithm for the Amazon 5-core Movies and TV dataset due to its ability to capture both collaborative and sequential patterns effectively. These findings suggest that the proposed NLP-based Biased SVD Recommender System effectively leverages the strengths of both NLP and Biased SVD to create a more robust and personalized recommendation engine.

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