A Novel Scheme for Movie Recommendation System using User Similarity and Opinion Mining

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Abstract---* *Movie recommender system has become an interesting research topic due to the growth of users in a mobile environment. To recommend movies, a complete aggregation of user's preferences, feelings (emotions), and reviews required to assist users for find best movies in more convenient way. However to deal with the recommendation system, we must consider timeliness and accuracy. In this paper, we propose a movie recommender system based on new user similarity metric and opinion mining. The primary objective of this paper is to find the type of opinions (positive, negative or neutral) for movies and also suggest top-k recommendation list for users. We extract aspect-based specific ratings from reviews and also recommend reviews to users depends on user similarity and their rating patterns. Finally, validating the proposed movie recommendation system for various evaluation criteria, and also the proposed system shows better result than conventional systems.

Index Terms—* *Movie recommender system, User similarity, Opinion mining, Aspect extraction, Top-k recommendation list

I. INTRODUCTION

Recommender systems are more popular and increase the production costs for many service providers. Today the world is an over-crowded so that the recommendations are required for recommending products or services. However recommender systems minimize the transaction costs and improves the quality and decision making process to users [1], [5], [6]. It is applied in various neighboring areas like information retrieval or human computer interaction (HCI). It gathers huge amount of information about user's preferences of several items like online shopping products, movies, taxi, TV, tourism, restaurants, etc. It stores information of different ways either positive or negative manner. It captures users review for watched movies, traveled places, and purchased products. When compare demand from the shopping products, service providers (travel, and restaurants), movie recommendation system design a big problem since other recommendation systems require fast computation and processing service from service providers and product distributors. To recommend movies, first collects the ratings for users and then recommend the top list of items to the target user [2]. In addition to this, users can check reviews of other users before watching movie. A different recommendation schemes have been presented includes collaborative filtering, content-based recommender system, and hybrid recommender system. However, several issues are raised with users posted reviews since it means various aspects about the film (director, film actors, music, sound and scenes). For example:

"The Dark Knight Rises is exciting, dark and creative – and well worth a few hours of your time"

The above mentioned sample review is the feedback of The Dark Knight Rises film released 2012. This review means the positive opinions about the film due to the presents of positive aspect of words like "EXCITING", "DARK" and CREATIVE. Depends on the various aspects, the viewer has different opinions. Hence, viewer reviews/ratings for a movie are highly preferred for recommender systems [3]. Sentiment analysis and opinion mining become interesting research topics that find the opinions of users all over world through analysis of reviews from online social networks (Facebook, Yahoo, etc.) [8]. Most of the recommender systems list opinions in chorological order (reverse). Therefore, a generic ranking technique is required from users to view tens/hundreds of reviews for one movie [4]. Online reviews of the university, smartphones and hotel services based semantic analysis is illustrated in [7].

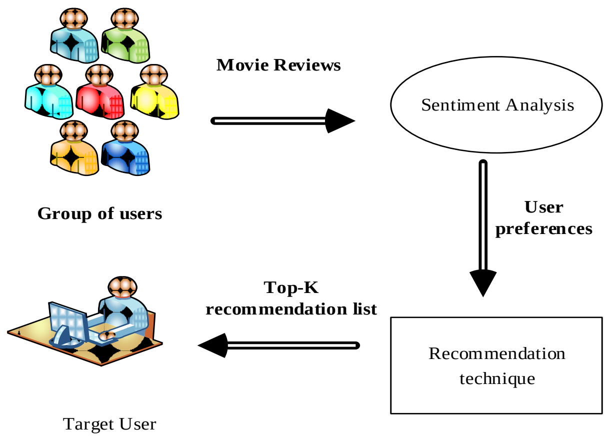

Figure.1. Sentiment Analysis based Recommendation System

Typically, the reviews consists of different users opinions in the form of natural language sentences. Therefore, it is more complex for users to view all the comments of users and also it is difficult to catch meaningful information from different opinions [9]. Fig.1 shows the recommendation

Revised Manuscript Received on December 22, 2018.

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system based on reviews (sentiment analysis). Over the last few decades personalized recommender systems have obtained great attention and very few researches have been proposed in this topic [19], [20]. In this paper, we have proposed two key concepts that design personalized movie recommendation system that are follows:

(1). we propose a novel scheme for extracting opinion-based movie similes from viewer-posted reviews.

(2). we design a recommendation system that provides a top-k list of items by user-movie similarity and review opinions.

The rest of this paper is organized as follows: In section 2 we have provided literature survey of this work. In section 3, we present the proposed system architecture with brief descriptions. In section, 4, we validate our experiments with comparison results. Finally, we conclude the paper.

II. LITERATURE REVIEW

Opinion mining based recommender systems suffered by many problems, but it improves accuracy by analyze individual user review data and also improves reliability by considered numerous opinions of viewers. To design a recommendation system using opinion mining we should be consider some key points: (i). detect sentiment expression correctly, and also properly mine words, features, adverbs, adjectives, and so on. (ii). Compute sentiment strength for semantic features or aspects accurately and result a normalized numerical value in some data dimensions. (iii). Suggest products or services accurately by viewers review and (iv). Require good generalization ability and high computational efficiency. Several researchers contributed different research kinds of work that are described briefly in this section. Xiu Li et al. [10] describes accurate recommendation system using opinion mining. They have discussed about current recommender systems and that are categorized into three categories: collaborative filtering, content-based recommendation, and knowledge-based recommendation. In collaborative filtering, the adjacent customers explore first and then provide the recommendation list. However, collaborative filtering does not consider certain attributes related to product or service. In content-based recommendation, the product features were extracted and it generates feature vectors. Afterwards, it generates feature vectors. The drawback of this approach is that it does not taken users behavior or activity towards the product, which leads to get the poor accuracy during recommendation. In knowledge based recommendation, users propose the demand first and the entire process in interactive strongly. This type of recommendation is also poor for new users and its more time consuming process. Sachin et al. [11] have presented a novel recommender systems based on personalized sentiment mining. They considered users personal sentiments and judgments to make the recommendations. There are different methods such as unigrams, bigrams, Bernoulli, naïve bayes, support vector machine and random forests on two datasets (Yelp and MovieLens). The proposed ALS (alternate least square) method and sentiment generation scheme were provides lesser RMSE than other methods, but when number of users increase and items to recommend, the time consumption is also increases and computational overhead has occurred. Yibo et al. [12] proposed a sentiment-enhanced hybrid recommender system (SEHRS) for movie recommendation over big data analytics framework. Firstly, a hybrid recommendation method is used to generate a preliminary list of recommendations of users. Secondly, sentiment analysis was presented to optimize the list. A big data analytics based framework was provides fast and convenient environment for users to extract suggestions about movies. Hriday et al. [13] proposed optimization algorithm called particle swarm optimization (PSO) for movie recommendation system. Kang Liu et al [14] proposed word alignment model for co-extracting opinion targets and opinion words from online reviews. A graph-based co-ranking algorithm was presented to find opinion relations and also word alignment process. Finally, the items with higher rank values are mined. In [15] travel recommendation system is proposed on which lists of best locations are shared for users. User behavior and activity based personalized recommender system is proposed which named ABiPRS. To improve the proposed travel recommendation system, multiple recommender systems were merged and validated the results for two real-time large scale datasets (TripAdvisor and Yelp). Jenq-Haur et al. [16] presented a sentiment rating scheme in order to find the exact rating of a movie. For that reason, they have facilitated sentiment lexicons adjustment, which improves the classification accuracy. Hui Li et al. [17] proposed an intelligent movie recommendation system by group-level sentiment analysis on microblogs. In this paper, the similarity between TV episodes and online movies were evaluated. The proposed intelligent approach presented effort to bridge the gap between TV and movie watchers. This work was applied in different real world applications such as online TV and movie program recommendation, add and service recommendation, home and mobile device personalization, and intelligent television system with social activity

Filipa et al. [18] presented a new recommender system which integrates movie ratings and unrated reviews on the web. Sentiment analysis was incorporated to offer user preferences analysis where the reviews were not associated with an explicit rating. A recommendation algorithm was proposed which performs based on matrix factorization with singular value decomposition (SVD). This work was implemented on two real-life datasets Amazon entertainment media (698210 reviews – 26% unrated) and IMDb (53112 reviews – 50% unrated). Amel et al. [21] proposed a multilingual recommender system via sentiment analysis, which helps Algerian users who choose products, movies, restaurants and other services based on online product restaurants. In this work both sentiment analysis and recommender system was integrated which deals with the huge number of users with provide accurate recommendation list. However, both research areas were suffered due to unlabeled data. Davide et al. [22] presented a sentiment-based approach to recommendation of Twitter users. This proposed sentiment-based approach was used weighting function called sentiment-volume-objectivity (SVO) function. It considers user attitude and also his/her reviews about the product or service. This weighting function aims to construct the richer user profiles to apply in the recommendation application, but it leads to lack of sentiment analysis and provide relatively poor recommendation to users. Thus, in this paper we overcome the limitations of above mentioned previous works.

III. PROPOSED WORK

3.1 Problem Definition

In this work, we focused on opinion mining based movie recommender system, which goal is to find the opinion (positive, negative and neutral) for the given review. The proposed method resolves the accuracy problem by combined technique. It considers domain specific aspects, linguistic rules, verbs, nouns, adverbs, and adjective together for mining opinions from reviews. The sentiment score for each feature is computed and then produce a final recommendation list for target user who request recommendation to visit movies.

3.2 System Overview

The proposed model is depicted in figure 2. In this section, our proposed research methodology for movie recommendation system is proposed.

A. Data Preprocessing

Reviews from users are real-life data which requires necessary pre-processing steps (cleaning, integration, transformation, etc.). In this paper, various preprocessing steps (word segmentation, stop-words removal, stemming, POS tagging, and representation of reviews) are applied to preprocess raw movie reviews.

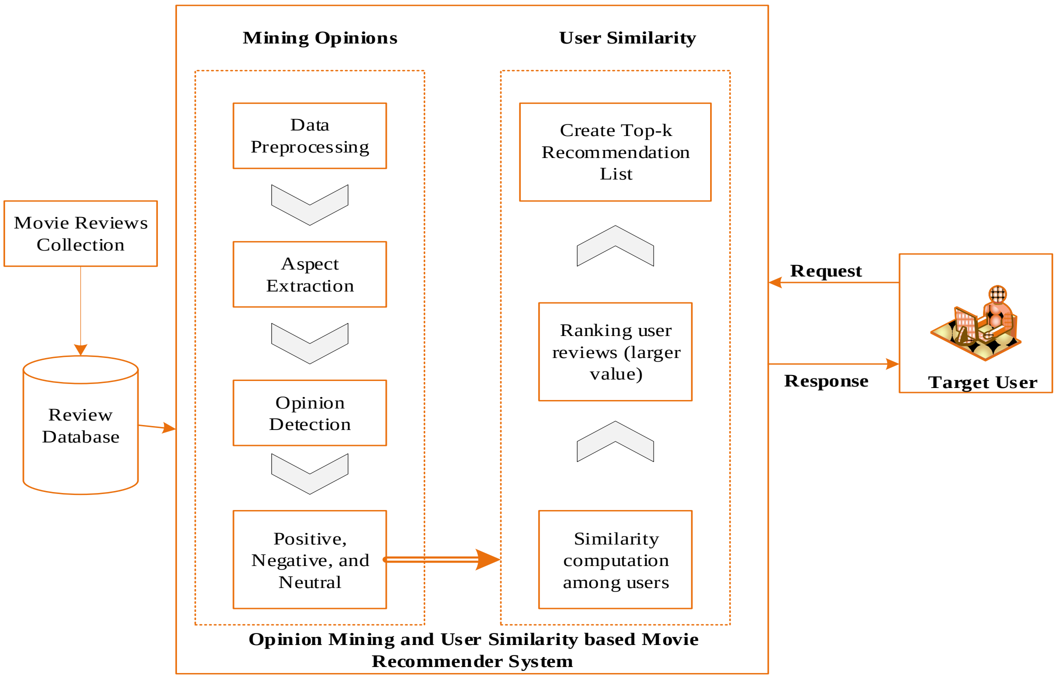

Figure.2. System Architecture

- **Word segmentation:** In movie review dataset, we need consider the word segmentation process for a given sentence due to lack of delimiters between words. In this work, we use WORDNET tool to finish the word segmentation process. Word net is a natural language processing (NLP) processing tool which is applied in different applications (text mining, named entity recognition, information retrieval, etc.).
- **Stop words removal:** Stop words are words that does not shows any specific meanings like a, at, the, is, to, for, etc. Commonly, these words are removed from a given sentence since increase the overhead in recommendation and increase storage space. When eliminate these words, we can increase the system performance in terms of storage space, and scalability.
- **Stemming:** It is a required process in all kind of retrieval, which reduces the reflected words and output the root word also referred as "stem". In addition to this lemmatization is also considered which further reduce the inflectional forms.
- **POS (Part-of-Speech) Tagging or POST:** We evaluate POS (noun, adverb, adjective, verb, etc.) for a given sentence. Thus the property of some word is identified from a sentence. We use more fine-grained POS tags (noun-plural).
- **Representation of Reviews:** In this process, each review generates bag-of-words model in which the order of words are eliminated. Assume that the number of words referred as "n" and hence the review can be denoted as n-dimension vector. The TF-IDF (Term-Frequency and Inverse Document Frequency) is applied to compute each word necessary in a given review.

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TF computes term occurrence frequency in one document. For a term w_i in document D_j, the TF_{ij} is defined as follows:

$$TF_{ij} = \frac{n_{ij}}{\sum an_{a,j}} \quad (1)$$

where n_{ij} is the number of term w_i occurrences in document D_j, a is the total number of words in document D_j. Subsequently, we compute IDF in which word importance is calculated in all documents. For a term w_i, IDF_i can be expressed as follows:

$$IDF_i = \log \frac{N}{\{j: w_i \in D_j\}} \quad (2)$$

where N is total amount of documents, $\{j: w_i \in D_j\}$ is the amount of documents which holes term w_i. Finally we compute TF-IDF is defined as.

$$TF - IDF = TF_{i,j} \times IDF_i \quad (3)$$

B. Aspect Extraction

Aspects are also known as important features reviewed by viewers. For each aspect, aspect-oriented opinion mining is used to measure the review opinions or polarity (positive, negative or neutral). In this step, data from different users are collected and stored in database. From the review database, it is evaluated and categorized to be implicit aspect or explicit aspect. When the aspect appeared in the sentence (e.g. the movie plot awesome), we directly extract the word. In the example, the term movie plot refers aspect which explicitly used in a sentence. In the review "the story is boring", boring refers to aspect mood, which indirectly appeared in the sentence.

C. Opinion Detection

In this phase we classified each term into appropriate opinion like positive, negative or neutral. In order to classify various aspects into opinions, we propose Naïve Bayes based Support Vector Machine (NbSVM), which is the combination of two classifiers where we can obtain better performance than SVM and NB. The dual problem of NbSVM is very similar to standard SVM algorithm. Kernel function is the major difference $K(x_i, x_p)$, which is defined n set of features of NbSVM The discriminant function $F^c(x)$ is defined by

$$F^c(x) = \sum_i A_i^C \, y_i \sum_{j \in x_i} k(x_i, x_{i,j}) + b \quad (4)$$

For multiclass SVM, the discriminant function $F^c(.)$ is learned for each class C using the same equation computed above. For example

Users Review (Input): The "Avengers: Infinity War" is a great movie since this film tells story about the vibranium that gave them wisdom, technology and knowledge. The entire theatre laughed. I saw most of his film because I have been a long-time fan of the Marvel film franchise. The sound of this film is crazy. In this file, there is huge amount of profane, crude language and violence. Hence I cannot recommend this movie and also this film tells about the classic story.

Three Categories of Opinions: "Avengers: Infinity War"

Positive: The "Avengers: Infinity War" is a great movie since this film tells story about the vibranium that gave them wisdom, technology and knowledge.

Negative: The sound of this film is crazy. In this file, there is huge amount of profane, crude language and violence. Hence I cannot recommend this movie and also this film tells about the classic story

Neutral: The entire theatre laughed. I saw most of his film because I have been a long-time fan of the Marvel film franchise

D. User Similarity Computation and Recommendation

Finally, similarity among users is computed using weight adjusted cosine score metric. Next we construct similarity matrix for users. Reviews are ranked based on descending of value. A larger value indicates that both two users are more similar in terms of movie reviews. Then we create the top-k recommendation list for target user and respond to them. In this way, we suggest list of movies for target user

IV. EXPERIMENTS

To verify our proposed approach performance, we evaluated experiments on movie datasets with JDK 1.8. The proposed system is running on Pentium ® Dual-Core CPU E5200 @2.50GHz with 1.00 GB RAM and 32-bit Windows 7 Ultimate Operating System. In this paper, we considered *"MovieLens"* review database.

4.1 Dataset Description

MovieLens database is concerned in this paper for evaluation, which is a standard datasets and gathered in 5-point rating scale and 5-star rating indicates highly liked and 1-star indicates most disliked.

TABLE.1.DESCRIPTION OF THE MOVIELEN BENCHMARK DATABASE

Name	Users	Movies	Ratings	Dates	Density
ML100K	943	1,682	100000	'97-'98	6.30%

4.2 Results and Discussion

In this we describe the results of our proposed work in terms of various metrics. Firstly we define the performance metrics which are used in this work and then we have validated the proposed work with previous works for comparison.

A. Performance Metrics

We evaluate the proposed system performance in terms of four metrics: precision, recall, f-measure, and f-measure that are defined as follows:

- **Precision (P)**: It is a measure of recommended movies relevant to the target user and it is represented in percentage (%). In other words, known positive predictive value is called precision. It is computed as follows:

$$P = \frac{|R(u) \cap r(u)|}{|R(u)|} \quad (5)$$

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where u represents the target user, $R(u)$ represents the recommended movies to the target user u and $r(u)$ represents the relevant movies list for the target user.

- Recall (R): It is a measure of the most relevant movies that are recommended for a target user is called recall. It is also referred as sensitivity. It is computed as follows:

$$R = \frac{|R(u) \cap r(u)|}{|r(u)|} \quad (6)$$

- **F-measure (F):** It is the Harmonic mean value from computed recall and precision. It is computed as follows:

$$F = 2 \times \frac{P \times R}{P + R} \quad (7)$$

- **Accuracy (A):** It is one of the important metric that consider for decision making. Here the accuracy for recommendation system is calculated based on the recommendation found during ranking. It is computed as follows:

$$A = \frac{\sum TP + \sum TN}{\sum TP + \sum FP + \sum FN + \sum TN} \quad (8)$$

where $\sum TP$ represents the sum of true positives, $\sum TN$ represents the sum of true negatives, $\sum FP$ represents the sum of false positives, and $\sum FN$ represents the sum of false negatives.

B. Comparison Results

In this section, we made the comparison for proposed system with the previous works ALS, and SEHRS. The main intention of this paper is to determine the top rank list of movies for a target user since we focus on the accurate retrieval of movies and also meet target user requirements. The attained proposed work results are depicted in table.2 and the figures of 3, 4, 5, 6 and table.3 are illustrated the comparison of precision, recall, f-measure, and accuracy, respectively. Furthermore, table 2 depicts the execution time for proposed with ALS, and SEHRS.

TABLE.2. EXPERIMENT RESULTS FOR PROPOSED WORK

Performance metric	Values
Precision	91%
Recall	89%
F-measure	89%
Accuracy	93.45%

TABLE.3. EXPERIMENT RESULTS FOR PROPOSED WORK

Approaches	Precision	Recall	F-measure	Accuracy
ALS	80.12%	70.26%	74.87%	91.7%
SEHRS	81.8%	74.4%	78.0%	89.9%

TABLE.4. EXECUTION TIME FOR PROPOSED VS. ALS AND SEHRS

Approaches	Execution time (in Seconds)
ALS	29.34
SEHRS	16.23
Proposed	**7.84**

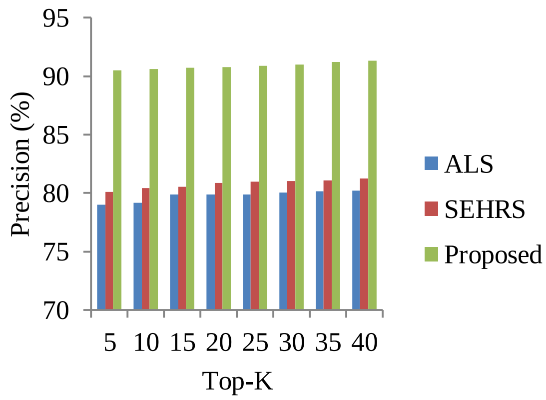

Figure.3. Comparison on Precision

Regarding experiments of proposed vs. previous recommendation system, the precision is relatively high (91%) than ALS (80.12%) and SEHRS (81.8%), which is shown in figure.3.

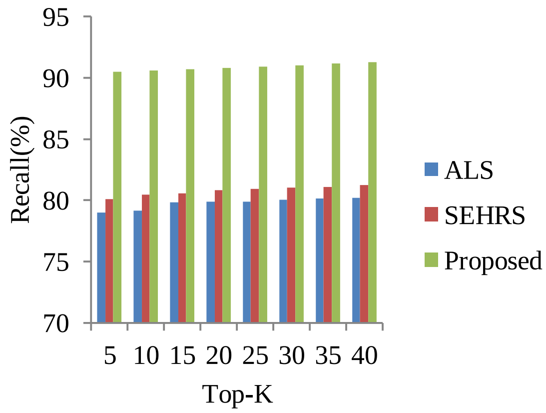

Figure.4. Comparison on Recall

For recall metric, we obtained 89% for proposed system which is better than ALS and SEHRS. Both recommendation systems increases computational overhead and minimize the system efficiency.

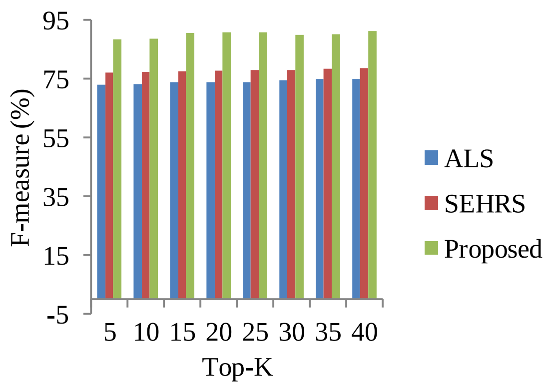

Figure.5. Comparison on F-measure

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Compared to ALS, and SEHRS, our proposed system obtained higher performance in terms of f-measure because we mined opinions on the basis of aspects, which improve the f-measure rate. We obtained 89% of f-measure than 74.87%, and 78.0% for ALS, and SEHRS, respectively.

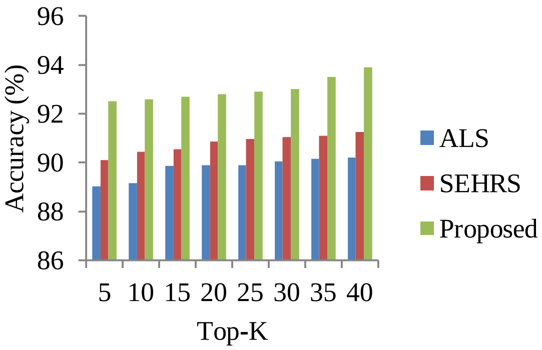

Figure.6. Comparison on Accuracy

Concerning the obtained computation accuracy, ALS and SEHRS proposed worst recommendation algorithm, which lack of preprocessing and aspect extraction in mining top-k recommendations. Execution time is also important metric to predict the system performance, which must be less for better recommendation system. We obtained accurate top-k result in 7.84seconds, which is less compared to ALS (29.34seconds) and SEHRS (16.23seconds). Compared the experimental results of various performance metrics, our proposed recommendation algorithm attained better performance than other algorithms such as ALS and SEHRS with the precision, recall, f-measure and accuracy.

V. CONCLUSION

In this paper, we intend to present a movie recommendation system based on the combination of opinion mining and user similarity analysis. This system helps to recommend top-k movies for target user. In this work, we collect reviews of users for movies and pre-process data with certain major preprocessing steps. The preprocessed are given for explicit and implicit aspect extraction. The aspect of a word is further classified according to the classes. Finally, top-k movies are recommended for target user. The results suggested by our proposed system are leading and block buster movies and the system is helpful for millions and billions of users around the globe. Here the accuracy of classification is improved using NbSVM classifier and also meet the requirement of the users. We have tested our proposed system on Movie Lens Dataset and also our work shows better performance than ALS and SEHRS.

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