MOVIE RECOMMENDATION SYSTEM

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Abstract: Recommendation systems (RSs) have garnered immense interest for applications in e-commerce and digital media. Traditional approaches in RSs include such as collaborative filtering (CF) and content-based filtering (CBF) through these approaches that have certain limitations, such as the necessity of prior user history and habits for performing the task of recommendation. To minimize the effect of such limitation, this article proposes a hybrid RS for the movies that leverage the best of concepts used from CF and CBF along with sentiment analysis of tweets from microblogging sites. The purpose to use movie tweets is to understand the current trends, public sentiment, and user response of the movie. Experiments conducted on the public database have yielded promising results.

Index Term: - Machine Learning algorithms, Recommendation systems, content-based filtering

I Introduction

Traditional approaches in RSs include such as collaborative filtering (CF) and content-based filtering (CBF) through these approaches that have certain limitations, such as the necessity of prior user history and habits for performing the task of recommendation. Users often face the problem of excessive available information. Recommendation systems (RSs) are deployed to help users cope up with the information explosion. RS is mostly used in digital entertainment, such as Netflix, Prime Video, and IMDB, and e-commerce portals such as Amazon, Flipkart, and eBay. In this article, we focus on RS for movies, which is an important source of recreation and entertainment in our life. Movie suggestions for users depend on Web-based portals. Movies can be easily differentiated through their genres, such as comedy, thriller, animation, and action. Another possible way to categorize the movies based on its metadata, such as release year, language, director, or cast. Most online video-streaming services , provide personalized user experience by utilizing the user's historical data, such as previously viewed or rated history. The purpose to use movie tweets is to understand the current trends, public sentiment, and user response of the movie. Experiments conducted on the public database have yielded promising results.

. 2 Literature survey

2.1 Analyzing user modeling on Twitter for personalized news recommendations

AUTHORS: F. Abel, Q. Gao, G.-J. Houben, and K. Tao.

How can micro-blogging activities on Twitter be leveraged for user modeling and personalization? In this paper we investigate this question and introduce a framework for user modeling on Twitter which enriches the semantics of Twitter messages (tweets) and identifies topics and entities (e.g. persons, events, products) mentioned in tweets. We analyze how strategies for constructing hashtag-based, entity-based or topic-based user profiles benefit from semantic enrichment and explore the temporal dynamics of those profiles. We further measure and compare the performance of the user modeling strategies in context of a personalized news recommendation system. Our results reveal how semantic enrichment enhances the variety and quality of the generated user profiles. Further, we see how the different user modeling strategies impact personalization and discover that the consideration of temporal profile patterns can improve recommendation quality.

2.2 Twitter-based user modeling for news recommendations

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the variety and quality of the generated user profiles. Further, we see how the different user modeling strategies impact personalization and discover that the consideration of temporal profile patterns can improve recommendation quality.

2.3 Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. AUTHORS: G. Adomavicius and A. Tuzhilin.

This paper presents an overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches. This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multicriteria ratings, and a provision of more flexible and less intrusive types of recommendations.

2.4 Enhancing deep learning sentiment analysis with ensemble techniques in social applications.

AUTHORS: O. Araque, I. Corcuera-Platas, J. F. Sánchez-Rada, and C. A. Iglesias. Deep learning techniques for Sentiment Analysis have become very popular. They provide automatic feature extraction and both richer representation capabilities and better performance than traditional feature based techniques (i.e., surface methods). Traditional surface approaches are based on complex manually extracted features, and this extraction process is a fundamental question in feature driven methods. These long-established approaches can yield strong baselines, and their predictive capabilities can be used in conjunction with the arising deep learning methods. In this paper we seek to improve the performance of deep learning techniques integrating them with traditional surface approaches based on manually extracted features. The contributions of this paper are sixfold. First, we develop a deep learning based sentiment classifier using a word embeddings model and a linear machine learning algorithm. This classifier serves as a baseline to compare to subsequent results. Second, we propose two ensemble techniques which aggregate our baseline classifier with other surface classifiers widely used in Sentiment Analysis. Third, we also propose two models for combining both surface and deep features to merge information from several sources. Fourth, we introduce a taxonomy for classifying the different models found in the literature, as well as the ones we propose. Fifth, we conduct several experiments to compare the performance of these models with the deep learning baseline. For this, we use seven public datasets that were extracted from the microblogging and movie reviews domain. Finally, as a result, a statistical study confirms that the performance of these proposed models surpasses that of our original baseline on F1-Score.

2.5 Hybrid recommender systems based on content feature relationship

AUTHORS: E. Aslanian, M. Radmanesh, and M. Jalili

Recommendation systems get ever-increasing importance due to their applications in both academia and industry. The most popular type of these systems, known as collaborative filtering algorithms, employ user-item interactions to perform the recommendation tasks. With growth of additional information sources other than the rating (or purchase) history of users on items, such as item descriptions and social media information, further extensions of these systems have been proposed, known as hybrid recommendation algorithms. Hybrid recommenders use both user-item interaction data and their contextual information. In this work, we propose new hybrid recommender algorithms by considering the relationship between content features. This relationship is embedded into the hybrid recommenders to improve their accuracy. We first introduce a novel method to extract the content feature relationship matrix, and then the collaborative filtering recommender is modified such that this relationship matrix can be effectively integrated within the algorithm. The proposed algorithm can better deal with the cold-start problem than the state-of-art algorithms. We also propose a novel content-based hybrid recommender system. Our experiments on a benchmark movie dataset show that the proposed approach significantly improves the accuracy of the system, while resulting in satisfactory performance in terms of novelty and diversity of the recommendation lists

3. Implementation Study

Many RSs have been developed over the past decades. These systems use different approaches, such as CF, CBF, hybrid, and sentiment analysis to recommend the preferred items. These approaches are discussed as follows. A. Collaborative, Content-Based, and Hybrid Filtering Various RS approaches have been proposed in the literature for recommending items [48]. The primordial use of CF was introduced in [18], which proposed a search system based on document contents and responses collected from other users. Yang et al. [59] inferred implicit ratings from the number of pages the users read. The more pages read by the users, the more they are assumed to like the documents. This concept is helpful to overcome the cold start problem in CF. Optimizing the RS is an ill-posed problem. Researchers have proposed several optimization algorithms, such as gray wolf optimization [26], artificial bee colony [21],

particle swarm optimization [53], and genetic algorithms [6]. Katarya et al. and Verma [26] developed a collaborative movie RS based on gray wolf optimizer and fuzzy c-mean clustering techniques. Both techniques are applied to the Movielens data set and predicted a better RS. They improved the existing framework in [24] proposing an artificial bee colony and k-mean cluster (ABC-KM) framework for a collaborative movie RS to reduce the scalability and cold start complication.

DISADVANTAGES OF EXISTING SYSTEM:

1. The existing users not only receive information according to their social links but also gain access to other user-generated information.

2. The necessity of prior user history and habits for performing the task of recommendation. Most of these studies are theoretical analysis at the macro level and there is a lack of quantitative investigations.

3.1proposed methodology

PROPOSED SYSTEM

The proposed sentiment-based RS is shown in Fig. 1. In this section, we describe various components of the proposed RS. A. Data Set Description The proposed system needs two types of databases. One is a user-rated movie database, where ratings for relevant movies are present, and another is the user tweets from Twitter.

1) Public Databases: There are many popular public databases available, which have been widely used to recommend the movies and other entertainment media. To incorporate the sentiment analysis in the proposed framework, the tweets of movies were extracted from Twitter against the movies that were available in the database. Experiments conducted using various public databases, such as the Movielens 100K,2 Movielens 20M,3 Internet Movie Database (IMDb,4) and Netflix database,5 that were not found suitable for our work due to the absence of microblogging data. After a thorough assessment of the abovementioned databases, the MovieTweetings database [12] was finally selected for the proposed system. MovieTweetings is widely considered as a modern version of the MovieLens database. The purpose of this database is to provide an up-to-date movie rating so that it contains more realistic data for sentiment analysis. Table I displays the relevant details of the MovieTweetings database.

2) Modified MovieTweetings Database: In the proposed work, the MovieTweetings database is modified to implement the RS. The primary objective to modify the database was to use sentiment analysis of tweets by the users, in the prediction of the movie RS. The MovieTweetings database contains the movies with published years from 1894 to 2017. Due to the scarcity of tweets for old movies, we only considered the movies that were released in or after the year 2014 and extracted a subset of the database which complied with our objective.

ADVANTAGES OF PROPOSED SYSTEM:

1.To use movie tweets is to understand the current trends, public sentiment, and user response of the movie.

2. Experiments conducted on the public database have yielded promising results.

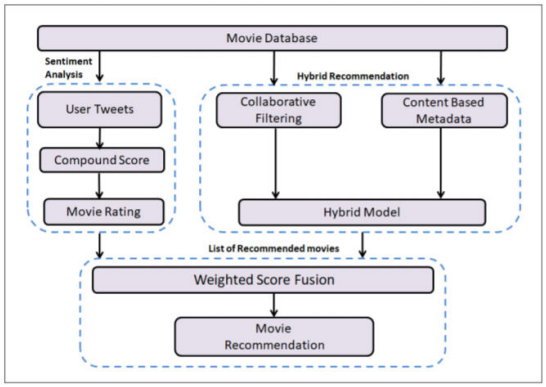

Fig 1: System Architecture

3.2 Methodology and Algorithms

MODULES:

1.Admin

In this module admin used to login,view all users and add sentiwords.

2.User

In this module user will register,login,search friends,requests,post,view all posts and Recommend Movies.

4 Results and Evolution Metrics

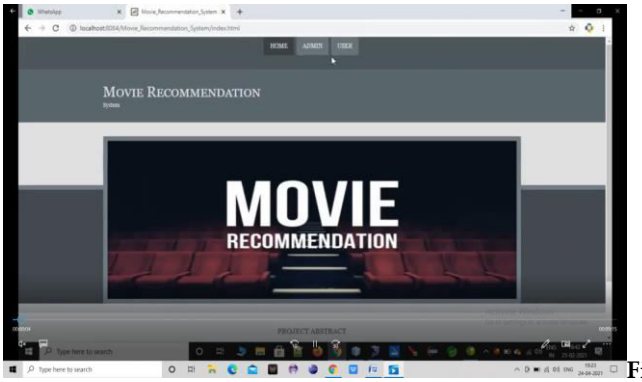

Fig2: Home screen:

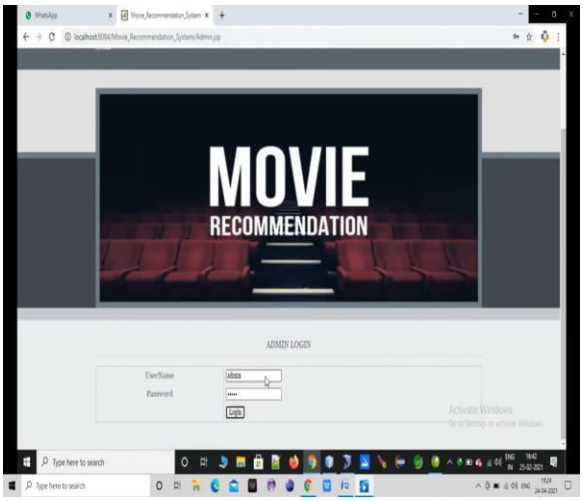

Fig3:Admin login page

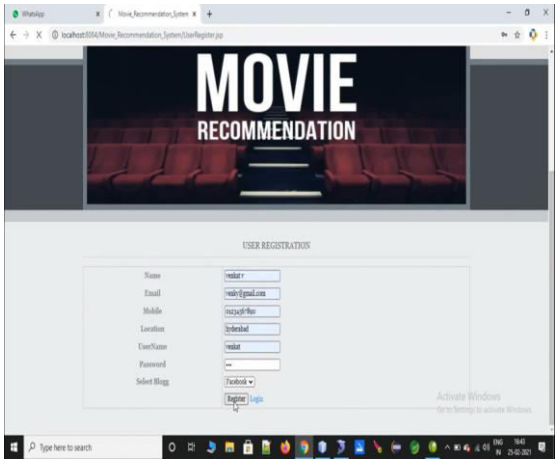

Fig 4: - Registration page

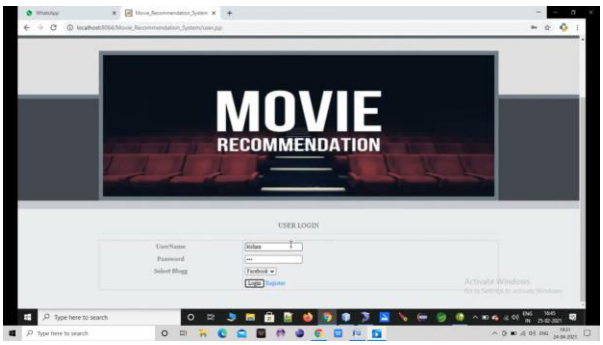

Fig 5 :- user login

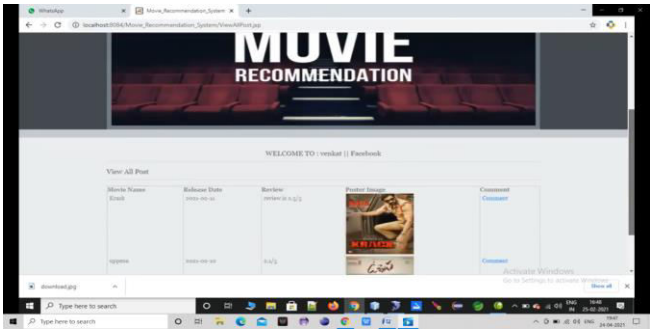

Fig 6 : Recommended movies

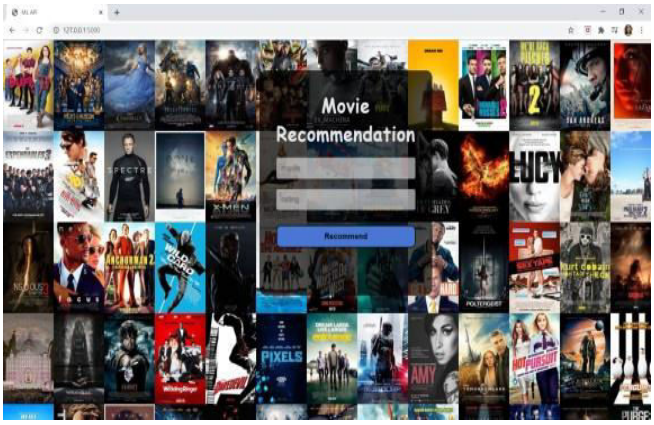

Fig 7 : User can search for recommended movies

5 Conclusion

RSs are an important medium of information filtering systems in the modern age, where the enormous amount of data is readily available. In this article, we have proposed a movie RS that uses sentiment analysis data from Twitter, along with movie metadata and a social graph to recommend movies. Sentiment analysis provides information about how the audience is respond to a particular movie and how this information is observed to be useful. The proposed system used weighted score fusion to improve the recommendations. Based on our experiments, the average precision in Top-5 and Top-10 for sentiment similarity, hybrid, and proposed model are 0.54 and 1.04, 1.86 and 3.31, and 2.54 and 4.97, respectively. We found that the proposed model recommends more precisely than the other models. In the future, we plan to consider more information about the emotional tone of the user from different social media platforms and non-English languages to further improve the RS.

6 References

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