

## MOVIE RECOMMENDATION SYSTEM USING SENTIMENT ANALYSIS FROM MICRO BLOGGING DATA

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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.

**Keywords:** *CF, CBF, RS, hybrid RS, MICRO BLOGGING DATA.*

### 1. INTRODUCTION:

In today's world, internet has become an important part of the human life. Users often face the problem of excessive available information. Recommendation systems (RS) are deployed to help users cope with this information explosion. RS are mostly used in e-commerce applications and knowledge management systems such as tourism, entertainment and online shopping portals. In this paper, we focus on RS for movies are 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 like comedy, thriller, animation, and action. Another possible way to categorize movies can be achieved on the basis of metadata such as year, language, director or by cast. Most online video-streaming services provide a number of similar movies to the user to utilising the user's previously viewed or rated history. Movie Recommendation Systems [23, 25, 48, 3, 53] help us to search our preferred movies and also reduce the trouble of spending a lot of time searching for favorable movies. The primary requirement of a movie recommendation system is that, it should be very reliable and provide the user with the recommendation of movies which are similar to their preferences. In recent times, with exponential increase in amount of

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onlinedata, RS are very beneficial for taking decisions in different activities of day-to-day life. RS are broadly classified into two categories: Collaborative filtering (CF) and Content-based filtering (CBF). It is a human tendency to take decisions on the basis of facts, predefined rules and known information which is available over the internet and this inclination of human behaviour gave rise to the concept of CF. Resnick et al. [37] introduced the concept of CF in netnews, to help people find articles they liked in a huge stream of available articles. CF help people make choices based on the perspective of other people. Two users are considered like-minded when their rating for items are similar whereas in CBF [46], items are suggested through the similarity among the contentual information of the items. With the advent of numerous social media platforms like Quora, Facebook, and Twitter, people are able to share their daily state of mind on the internet. Twitter [1, 2, 13] is one of the most popular social media platform founded in 2006 where users can express their thoughts in limited characters.

The Unique Selling Proposition of Twitter is that the existing users not only receive information according to their social links, but also gain access to other user-generated information. The source of information on Twitter is called tweets which are of limited-character that keep users updated about their favorite topics, people and movies. In this paper, we propose a movie recommendation framework by fusing hybrid and sentiment scores from Movie Tweetings database. The main contributions of the paper are as follows:

1. We propose a hybrid recommendation system by combining collaborative filtering and content-based filtering.
2. Sentiment analysis is used to boost up this recommendation system.
3. A detailed analysis of proposed recommendation system is presented through extensive experiment. Finally, a qualitative as well as quantitative comparison with other baselines models is also demonstrated.

## **2. LITERATURE SURVEY**

### **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

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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 Twitter-based user modeling for 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.

## **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

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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.

#### **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.

### **3. METHODOLOGY**

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.

### **PROBLEM DEFINITION**

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.

## OBJECTIVE OF PROJECT

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.

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.

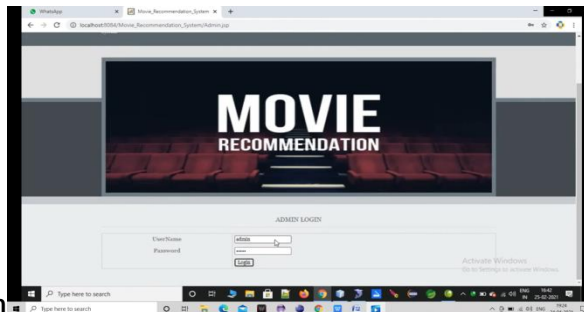
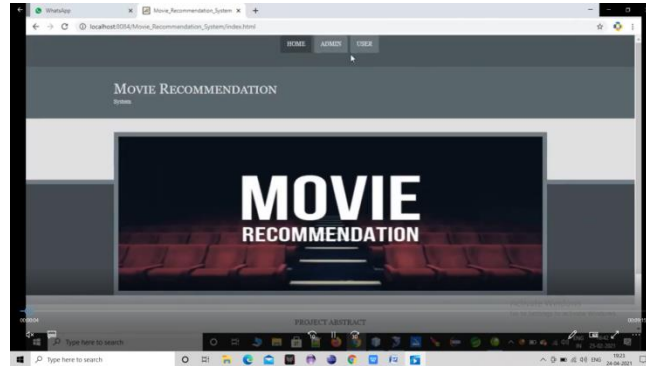
1) Public Databases: There are many popular public databases available, which have been widely used to recommend the movies and other entertainment media. To incorporate the sentiment analysis in the proposed framework, the tweets of movies were extracted from Twitter against the movies that were available in the database. Experiments conducted using various public databases, such as the Movielens 100K,<sup>2</sup> Movielens 20M,<sup>3</sup> Internet Movie Database (IMDb),<sup>4</sup> and Netflix database,<sup>5</sup> that were not found suitable for our work due to the absence of microblogging data. After a thorough assessment of the abovementioned databases, the MovieTweatings database [12] was finally selected for the proposed system. MovieTweatings 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 MovieTweatings database.

2) Modified MovieTweatings Database: In the proposed work, the MovieTweatings database is modified to implement the RS. The primary objective to modify the database was to use sentiment

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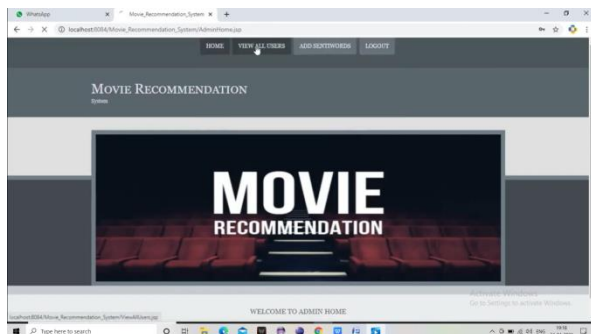
analysis of tweets by the users, in the prediction of the movie RS. The MovieTweets database contains the movies with published years from 1894 to 2017. Due to the scarcity of tweets for old movies, we only considered the movies that were released in or after the year 2014 and extracted a subset of the database which complied with our objective.

## Home Page



## Admin Loign

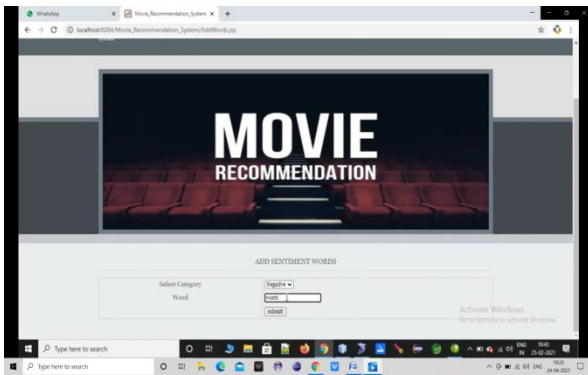
## Admin Page



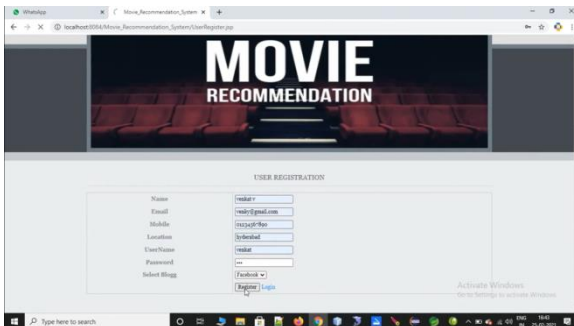
## View All Users



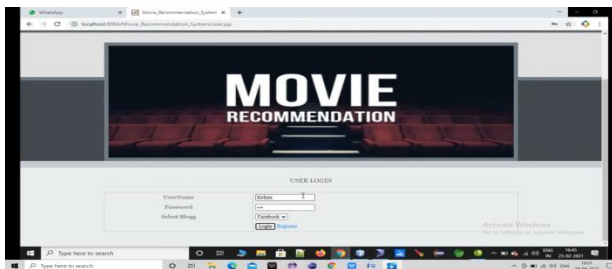
### Add Sentiment Words



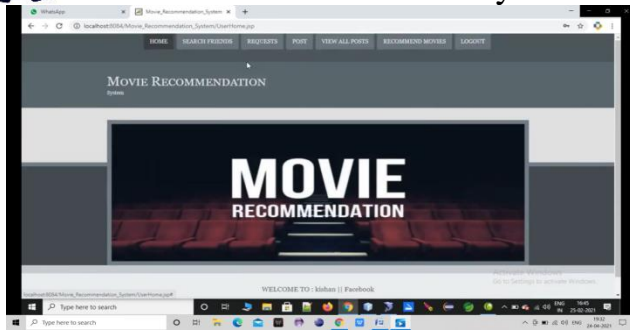
### User Registration



### User login



### User HomePage



## 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.

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