Review on Collaborative Filtering Machine Learning Approach for Recommendation Systems

Nikita Khare [1], Arun Jhapate [2]
[1] Department of Computer Science, Sagar Institute of Research & Technology, Bhopal, India
[2]Department of Computer Science, Sagar Institute of Research & Technology, Bhopal, India

* Corresponding Author: Nikita Khare

Abstract: - *Recommender systems, also known as recommendation systems, are a subclass of information filtering systems that use a model created from the characteristics of an item (content based approaches) or the user's social environment to predict the "rating" or "preference" that a user would give to an item (such as music, books, or movies) or social element (e.g. people or group) they had not yet considered (collaborative filtering approaches). Such recommendation systems are helpful for companies that collect information from a large number of customers and aim to offer the best recommendations. This paper provides the overview of recommendation system and different types of filtering system.*

Keywords: Recommendation System, VOD, OTT, Collaborative Filtering, Content-based filtering etc

I. INTRODUCTION

Recommender systems, also known as recommendation systems, are a subclass of information filtering systems that use a model created from the characteristics of an item (content based approaches) or the user's social environment to predict the "rating" or "preference" that a user would give to an item (such as music, books, or movies) or social element (e.g. people or group) they had not yet considered (collaborative filtering approaches). Although there have been many different approaches to recommender systems developed over the past few years, interest in this field is still high because of the growing need for real-world applications that can offer personalized recommendations and manage information overload [2]. In order to address these issues, numerous cutting-edge techniques are proposed, including content-boosted collaborative filtering, clustering-based filtering, combining item- and user-based similarity, and many others. Despite these developments, recommender systems still need to be improved, making this a fertile area for research.
An intelligent system called a recommendation system suggests products to users that they might find interesting. As can be seen in figure, some practical applications of such systems include recommending books, CDs, and other items on Amazon.com, movies by Movielens, music by Last.fm, and news at VERSIFI technologies.

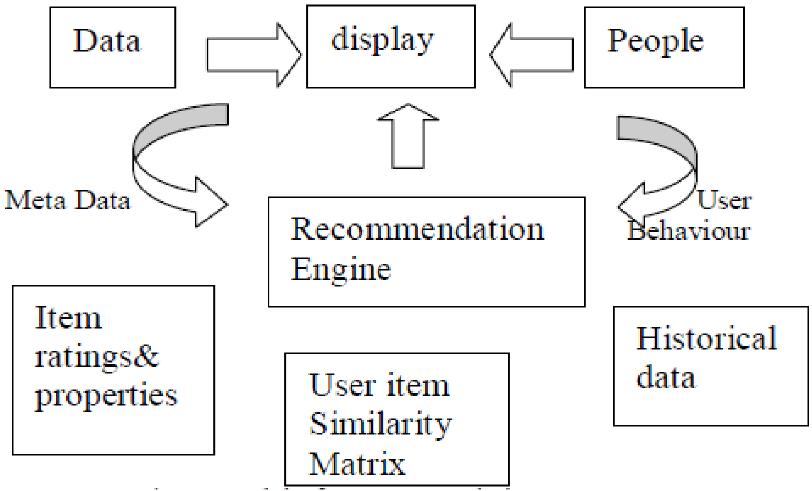

Figure 1 Model of Recommender System [2]

II. VIDEO ON DEMAND (VOD)

Users have grown accustomed to popular over-the-top video on demand (VOD OTT) services like Netflix and YouTube for online video distribution, and despite the potential for increased competition and abundance brought on by digital

technologies, a trend towards vertical integration of these international agents and partnerships with established players in the infocommunications industry is being observed. The term "over the top" is used to describe "the distribution of audio content, video content, and other media over the Open Internet, which is outside the control of network operators in the distribution of content." [4]. This definition covers a wide range of services, including social media, video sharing, search engines, email services, instant messaging, voice over IP (VoIP), online payment platforms, and search engines.
With the rise of VOD (Video on Demand) services and algorithmic automatizations driven, among other things, by the proliferation of SmartTVs, audiences around the world have been adapting new forms of content consumption. We have noticed that viewers, especially in Europe, are spending more and more time watching non-linear television (free, subscription, and transaction video on demand), while spending less and less time watching traditional linear TV.. Although the amount of time spent watching audiovisual content daily has increased overall, VOD services have reduced the amount of time spent watching traditional television in nations like the United Kingdom, Italy, and Spain. This trend is anticipated to intensify in the upcoming years due to the entry of new competitors like Apple and Disney, among others, at the end of 2019 and throughout 2020.

III. COLLABORATIVE FILTERING

Without the need for exogenous information about either users or items, collaborative filtering (CF) methods generate user-specific recommendations of items based on patterns of ratings or usage (such as purchases). We present several recent extensions that are available to analysts looking for the best possible recommendations, even though well-established methods still serve many purposes satisfactorily.

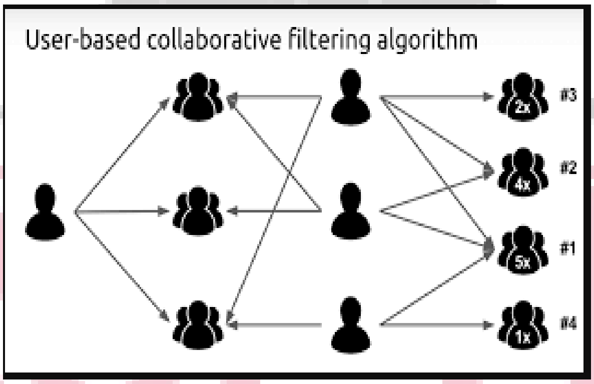

Figure 2 User based Collaborative Filtering [3]

Collaborative filtering is the process of selecting or assessing information based on the views of other individuals. Utilizing profiles allows for this filtering. Collaborative filtering techniques gather profiles, create them, and use similarity models to establish relationships between the data. User preferences, user behavior patterns, or item properties are some examples of potential categories for the data in the profiles.

IV. CONTENT-BASED (CB) FILTERING SYSTEM

People would want something exactly like it if they liked it. When determining the context and properties of each object is easy, it usually works well. The focus of content-based technologies is on the characteristics of things. By contrasting two objects' qualities, one can determine how similar they are. The method used the most frequently in the recommendations category is content-based filtering (CBF) [7]. The main focus of content-based technologies was on product attributes. By comparing the characteristics of the components, one can determine how similar they are. A product profile that captures key facets of the object is required in a content-based framework. The content analyzes the characteristics of the suggested products.- algorithm on basis. For instance, if a Netflix user has watched several western movies, they may suggest western-themed movies and television shows from the dataset. There are several ways to construct a recommending system based on suggested recommendations. For instance, machine learning techniques like Naive Bayes, support vector machines, and decision trees, as well as data collection technologies like Term Frequency (TF) or Inverse Document Frequency (IDF).

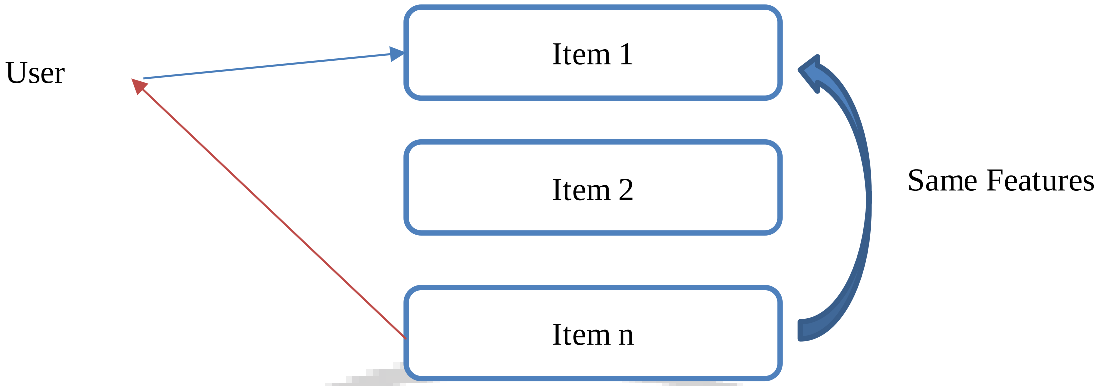

Figure 3 Content based filtering [7]

V. LITERATURE REVIEW

There is a description of recommender systems and a thorough explanation of collaborative filtering in [16]. It also outlines some of the drawbacks of conventional recommendation techniques and discusses hybrid extensions that combine users' spatial preferences with item-based collaborative filtering (user-based collaborative filtering). A wider variety of applications can use this hybrid system. It facilitates the user's quick and accurate discovery of the items of interest.

Recommender system (RS) is a ground-breaking method that has changed applications from being content-based to being customer-centric. It is a technique for locating what the customer wants, which could be information or a physical object. The development of recommendation techniques, which improve our understanding of users and clients, was made possible by our ability to gather and process information. The development of recommender frameworks over the past few years has resulted in a wealth of tools that encourage researchers and scientists to produce precise recommenders. Describes collaborative filtering in detail and provides an overview of recommender systems [17]. It also outlines some of the drawbacks of conventional recommendation techniques and discusses hybrid extensions that combine users' spatial preferences with item-based collaborative filtering (user-based collaborative filtering). A wider variety of applications can use this hybrid system. It facilitates the user's quick and accurate discovery of the items of interest.

Movies and videos are becoming more popular on social media and OTT platforms as a result of the proliferation of multimedia technologies around us, making it difficult for users to choose which one to watch. Systems that recommend movies are frequently used for this. Two-thirds of the movies watched on Netflix have been found to be those that its users have suggested. The purpose of this research is to recommend movies based on implicit user ratings, or feedback from other users. As a replacement logged-in user won't have information about their previous favorite movies, implicit feedback will improve Data Sparsity. [18]. As a result, suggesting movies to them based on their similarity to other users is frequently a plus. The expected outcome will depend on the optimistic outlook; if the predicted rating is high, it will be recommended; if not, it won't. The performance of the methodology is measured with accuracy and precision values for different strategies. It gives the best accuracy and highest precision values using Logistic Regression (LR) and lowest recall value as compared to other algorithms. This technique gives an accuracy, precision, and recall value of 81.9 percent , 69.82 percent , and 32.5 percent , respectively, using LR.

Recommendation systems, like the Netflix Recommender System (NRS), will become essential competitive elements for every significant over-the-top video streamer as the Streaming Wars intensify. As a result, semi-autonomous algorithmic technologies will increasingly control the creation and consumption of movies and television shows. But how do systems like the NRS for making recommendations work? What functions do they perform? And what effects are they having on the culture of film and television? This article will examine how algorithms are affecting taste-making processes and reevaluate some of the critical theoretical stances that have come to dominate the conversation about algorithmic cultures in order to address these questions. [19].

Users now face a deluge of content due to the proliferation of movie content platforms, making it challenging to choose the right movies. While there has been a lot of research into creating recommender systems that are effective at providing customers with personalized recommendations based on their past preferences and behaviors, users' sentiments and emotions have not received nearly as much attention. In [20], We created a graph-based movie recommender system that combined user ratings with sentiment and emotion data, and we assessed its performance against well-known conventional models. A modified version of BERT was used to extract the sentiment and emotion data. We made use of a Kaggle dataset that was produced by crawling the meta-data for movies and the Rotten Tomatoes website review data. The findings of the study demonstrate the superiority of the proposed models over the traditional models when emotion and sentiment are added. The findings of this study suggest that sentiment and emotion data may be combined in a movie recommendation system.

In [21], With an emphasis on mobile computing and AI techniques, we provide a thorough survey of recent developments in intelligent mobile Context-Aware Recommender Systems (mobile CARS), along with an analysis of current research gaps and future research directions. We concentrate on methods that utilize additional context information in addition to simply taking the user's location into account. In this study, we found that promising artificial intelligence models for mobile CARS are deep learning approaches. Additionally, in the near future, we anticipate push-based recommendation solutions to become more prevalent, where at least a portion of the recommendation engine could run on mobile devices, which could distribute data and tasks.

Recommender Systems are decision-support tools that use cutting-edge algorithms to assist users in discovering under-researched items that may be of interest to them. While recommender systems may provide a number of alluring advantages, they may also amplify undesirable outcomes, such as the Popularity Bias, in which a small number of popular users or items gain more popularity while a large number of unpopular users or items gain more unpopularity. In this article, we examine how various recommender algorithms affect the popularity bias in various application domains and recommendation scenarios. [9]. By taking into account two different recommendation scenarios—the user-based scenario (such as suggesting users to follow) and the item-based scenario—we have developed a thorough evaluation methodology (e.g., recommending items to users to consume). We compared a wide range of traditional and contemporary recommender algorithms using two sizable datasets, Twitter and Movielens, and a variety of metrics, including PR-AUC, RCE, Gini index, and Entropy Score.

VI. CONCLUSION

There are many different genres, civilizations, and languages available in the world of cinema. This highlights the issue of computer programs recommending movies to individuals. There has been a lot of work done in this field up to this point. There is, however, always room for development. A recommendation system is a program that, in response to particular data, suggests movies and web series across different OTT services. The qualities of previously liked films are typically used by movie recommendation systems to predict what movies a user will appreciate. Such recommendation systems are helpful for companies that collect information from a large number of customers and aim to offer the best recommendations. This paper provides the overview of recommendation system and different types of filtering system.

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