JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue

JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)

An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Movie Recommendation System

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Abstract: **Today, there is a sizably voluminous variety of different approaches and algorithms for data filtering and recommendations giving. Online content and accommodation providers deal with the quandary of providing "relevant" content on a customary substructure, especially due to the sheer volume of data available. This work deals with one such quandary, namely, that of soothsaying utilizer predilection for movies utilizing the Netflix database. We present a recollection-predicated Collaborative Filtering (CF) algorithm that learns the personality traits of the users in a features space we call the Latent Genre Space (LGS). This representation sanctions us to utilize traditional clustering algorithms in this space, and overcome one of the most sizably voluminous quandaries in these works – that of different lengths of utilizer feature vectors in the voting space. Inference techniques in this space are discussed, and a KD-tree predicated most proximate-neighbor scheme is implemented. In the terminus, we will show the main challenges recommender systems come across.**

Keywords **–collaborative filtering, content-based filtering, database, most proximate-neighbor, recommendation.**

I. INTRODUCTION

With the commencement of the Web 2.0 era, the cyber world commenced growing up and developing with tremendous haste. Many opportunities, such as sharing n erudition, information, and opinion with other users, emerged. This did favor the development of gregarious networks like Facebook. Nowadays, authors can apportion their engenderments with millions of readers around the globe. Tyro-musicians can get famous more expeditious than ever afore just by uploading their tracks. The business world has found more customers and profit in the cyber world. A variety of online shops, auctions, and flea markets opened up in the cyber world. Today, every utilizer of the World Wide Web can purchase virtually any item in any country of the world. As opposed to authentic shops, in the cyber world, there are no place constraints. There is a virtually illimitable place. Nevertheless, people came across an incipient quandary in the WWW. The amplitude of information and items got prodigiously and sizably voluminous, leading to an information overload. It became an immensely colossal quandary to find what the utilizer is genuinely probing for. Search engines partially solved that quandary, however, personalization of information was not given. So developers found a solution in recommender systems. Recommender systems are implemented for filtering and sorting items and information popular relegation of CF algorithms was proposed by Breese – into Recollection predicated and Model-predicated methods. Recollection-predicated methods work on the principle of aggregating the labeled data and endeavor to match recommenders to those seeking recommendations. Most prevalent recollection-predicated methods works are predicated on the notion of most proximate neighbor, utilizing a variety of distance metrics. Model-predicated methods, on the other hand, endeavor to learn a compact model from the training data, for example, learning parameters of a parametric posterior distribution. From an operational perspective, recollection-predicated methods potentially work with the entire training set and scale linearly with the magnitude of training data, while model-predicated methods are constant time.

	The Godfather	Memento	Titanic	Star Wars
John	5	1	2	5
Dave	4		2	2
Susane	5	1	2	?
Mark	2	2		4

Table 1: Table exhibiting the ratings that different users gave for the movies.

1) **Content based filtering**:-

Content-predicated recommender systems work with profiles of users that are engendered at the commencement. A profile has information about a utilizer and his taste. Taste is predicated on how the utilizer rated items. Generally, when engendering a profile, recommender systems make a survey, to get initial information about a utilizer to eschew the incipient-utilizer quandary. [2] In the recommendation process, the engine compares the items that were already positively rated by the utilizer with the items he didn't rate and probes for kindred attributes. Those items that are mostly homogeneous to the positively rated ones, will be recommended to the utilizer. Figure 1 shows an example of a utilizer profile with the movies he/she has visually examined and the ratings the utilizer made.

Figure 2 shows the list of movies and their attribute values. A content predicated recommender system would ascertain movies from the list (Figure 2) that the utilizer has already visually examined and positively rated. Then, it would compare those movies with the rest of the movies from the list (Figure 2) and look for kindred attributes. Homogeneous movies would be recommended to the utilizer. In the current example, we can optically discern that there is a movie ”Scary Movie” akin to the movie ”American Pie” that the utilizer positively rated. The utilizer hasn't rated ”Scary Movie” so it will be recommended to him/her.

Movies	Comedy	Violance	Horror	Explicit Content
American Pie	10	3	1	9
Scary Movie	8	8	4	9
Saw	2	10	10	7
...	...	...	...	...

Figure 2: The movies list

Movies	Green Lantern	Source Code	American Pie	Hangover 2
Ratings	8	7	9	10

Figure3: The movies the user has watched

There are different algorithms for quantifying kindred attributes among items in the database and those in the users' profiles. One of such approaches is the cosine kindred attribute. Representing items as vectors on a coordinate space it measures angles between vectors and gives out their cosine value. Vectors ~ WC and ~ ws of two items with attributes are compared in cosine homogeneous attribute function as follows: The more homogeneous the two items are, the more diminutive the angle between their vectors.

$$u(c,s) = cos(\vec{w}_c, \vec{w}_s) = \frac{\vec{w}_c \cdot \vec{w}_s}{||\vec{w}_c|| \times ||\vec{w}_s||} =$$

$$= \frac{\sum_{i=1}^{K} \vec{w_{ic}} \vec{w_{is}}}{\sqrt{\sum_{i=1}^{K} \vec{w_{ic}^2}} \sqrt{\sum_{i=1}^{K} \vec{w_{is}^2}}}$$

2) COLLABARATIVE FILTERING :-

Collaborative filtering became one of the most researched techniques of recommender systems since this approach was mentioned and described by Paul Resnick and Hal Varian in 1997. [1] The concept of collaborative filtering is in finding users in a community that shares appreciation [6]. If two users have the same or virtually the same rated items in prevalence, then they have homogeneous tastes. Such users build a group or a soi-disant neighborhood. A utilizer gets recommendations to those items that he/she hasn't rated afore, but that was already positively rated by users in his/her neighborhood. Figure 4 shows that all three users rate the movies positively and with homogeneous marks. That signifies that they have kindred tastes and build a neighborhood. The utilizer A hasn't rated the movie ”TRON: Legacy”, which probably denotes that he hasn't optically canvassed it yet. As the movie was positively rated by the other users, he will get this item recommended. As opposed to simpler recommender systems were recommendations based on the most rated item and the most popular item methods, collaborative recommender systems care about the taste of the utilizer.

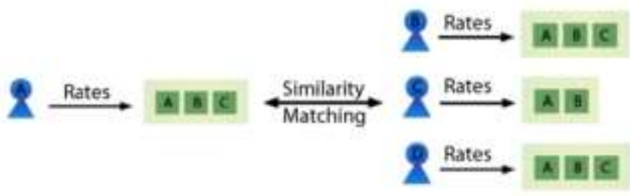


Figure 5: User-based collaborative recommender system

Item-predicated approach: This approach was proposed by the researchers of the University of Minnesota in 2001 [12]. Referring to the fact that the taste of users remains constant or changes very remotely homogeneous items build neighborhoods predicated on appreciations of users. Afterward, the system engenders recommendations with items in the neighborhood that a utilizer would prefer [12] [8]

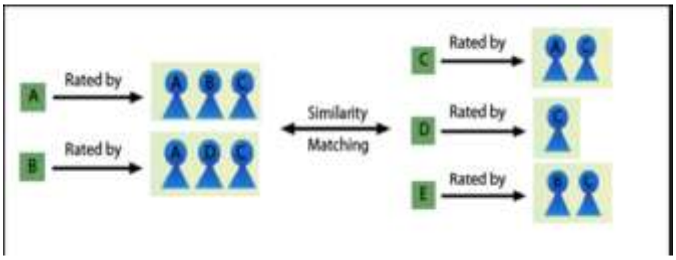


Figure 6: Item-predicated collaborative recommender system

Combination Recommendation Approaches Utilizing different methods is often cognate to the different recommendation issues. These quandaries are caused by four main instances that we endeavor to eschew by amalgamating collaborative and content-predicated techniques to compensate for each other's downsides. The main causes are incipient items, incipient users that understandably have not submitted or received any ratings. Sparsely due to immensely colossal data sets and little overlapping between users rating and determinately averaging effect e.g. due to long time content consumption and poor system design

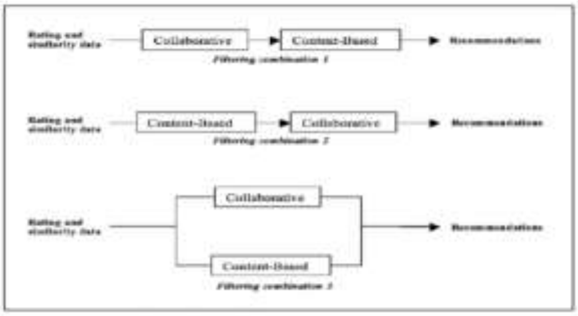
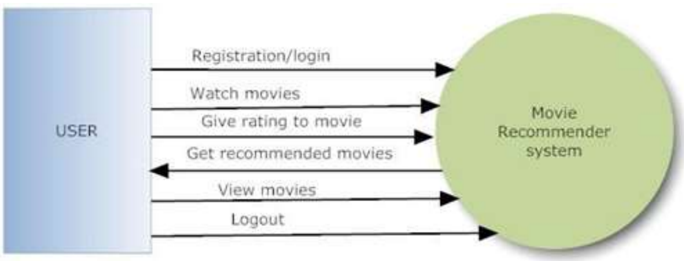


Fig. Different Ways of Combining CF and CBF

II. Literature Survey

The capacity of computers to provide recommendations was apperceived fairly early in the history of computing. Grundy, a computer predicated librarian, was an early step toward automatic recommender systems. It was fairly primitive, grouping users into “stereotypes” predicated on a short interview and utilizing hard-coded information about sundry Stereotypes' book predilections to engender recommendations, but it represents a consequential early ingress in the recommender systems space.In the early 1990s, collaborative filtering commenced arising as a solution for dealing with overload in online information spaces. The tapestry was a manual collaborative filtering system: it sanctioned the utilizer to query for items in an information domain, such as corporate e-mail, predicated on other users’ opinions or actions (“give me all the messages forwarded by John”). It required effort on the component of its users but sanctioned them to harness the reactions of anterior readers of a piece of correspondence to determine its pertinence to them. Automated collaborative filtering systems anon followed, automatically locating germane opinions and aggregating them to provide recommendations. Group Lens utilized this technique to identify Usenet articles that are liable to be intriguing to a particular utilizer. Users only needed to provide ratings or perform other overt actions; the system cumulated these with the ratings or actions of other users to provide personalized results. With these systems, users do not obtain any direct cognizance of other users’ opinions, nor do they require to ken what other users or items are in the system to receive recommendations. During this time, recommender systems and collaborative filtering became a topic of incrementing interest among human-computer interaction, machine learning, and information retrieval researchers. This interest engendered several recommender systems for sundry domains, such as Ringo for music, the Bellcore Video Recommender for movies, and Jester for japes. Outside of computer science, the marketing literature has analyzed recommendations for its faculty to increment sales and ameliorate customer experience. Research on recommender algorithms garnered paramount attention in 2006 when Netflix launched the Netflix Prize to amend the state of movie recommendations. The objective of this competition was to build a recommender algorithm that could beat their internal Cine Match algorithm in offline tests by 10%. It sparked a flurry of activity, both in academia and amongst hobbyists. The $1M prize demonstrates the value that vendors place on precise recommendations.

III. Proposed System



Phase 1: The users must start working in a special account in the system and enter the required information upon it (id, utilizer denomination, password, email,)

Fig. System Framework

Phase 2: After registration, the users can evaluate the movies by rating movies from 1 to 5. The users after optically discerning the component or the whole movie will decide on the movie according to his/her like, then rated between 1 to 5, as shown in Table

	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7
User 1	4	3	0	2.5	3.5	5	0
User 2	5	4	0	4.5	2.5	0	0
User 3	0	2.5	3	0	1	0	1.5
User 4	0	0	0	2.5	0	3.5	4
User 5	1	0	5	0	0	0	0

TABLE. User–Item Matrix Rating

Phase 3: This phase calculates an incipient hybrid recommender system that consists of CF and CBF with human emotions and our algorithm as shown in Fig.

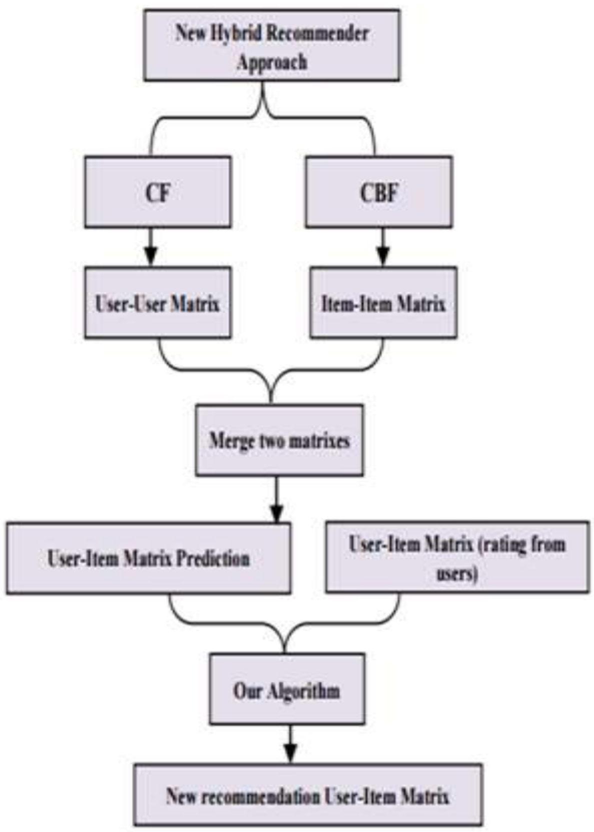


Fig. New Hybrid Recommender System

Figure 1. New Hybrid Recommender System

Hybrid Filtering:- A Hybrid approach is a combination of cooperative and content-based separating techniques while making ideas; the film's setting is additionally considered. The client-to-thing connection and the client-to-client connection likewise assume an imperative part at the hour of the suggestion. This structure gives film suggestions according to the client's information, gives one-of-a-kind proposals, and tackles an issue assuming the particular purchaser overlooks pertinent information. The client's profile information is gathered from the site, film's setting likewise considers the client's watching film and the information of the scores of the film. The information comprises conglomerating comparable computations. This strategy is known as the mixture approach, in which the two techniques are utilized to create the outcomes. Whenever this framework is contrasted and different methodologies, this framework has higher ideas exactness. The principal reason is the shortfall of data about the sifting's space conditions and individuals' advantages in a substance-based framework. Whenever these two methodologies cooperate, you will get more information, prompting better outcomes; it investigates the new ways to huge hidden content and cooperative sifting strategies with purchaser conduct information. This framework has taken to execute both the frameworks and defeat a large portion of the shortcomings of every framework's calculations and works on the framework's exhibition.

IV. Result And Discussion

The purpose of this system was to ease the movie finding and recommendation process. Movie Recommendation System being a web app give the User the comfort to find movie from any device, the User just needs an active internet connection. We have kept the interface simple yet appealing at the same time. This chapter includes the snapshots of the actual outputs that were seen by the user and this chapter also contains the results of the proposed system.

Fig 4.1 shows the home page wherein users can get information about the. User can navigate to 'View Movies' or 'Trending Movies' as shown in figure .

Figure 4.1 Home Page of Movieo

As shown in Fig 4.2.1 From this page the user or the admin can log in and register

Figure 4.2.1 Login Page

Below figure 4.2.2 shows the Collection of movies in the database, from where the user can choose to rate the movie

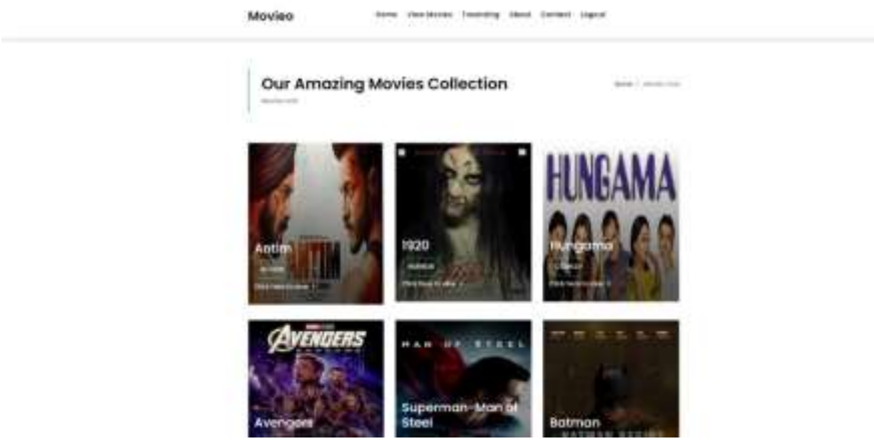


Figure 4.2.2. movie collection

Below figure 4.2.3 shows the selected movie and the user and give rating and review

Figure 4.2.3. Rating&Review

Below figure 4.3 Shows the result of the Recommended Movies

Figure 4.3 Recommended Movies

V. Conclusion

In this project, we designed a new web recommender system for movies based on emotion. The movies are complex objects and emotions are human interaction, which is difficult to combine together. In this paper, we applied a matrix for integrating movie recommendations by a hybrid approach, which consists of a CBF and CF system with an emotion detection algorithm and our algorithm. Furthermore, our algorithm calculated the user rating 1 and 5 because the users absolutely liked or disliked the movies. This system gives much better recommendations to users because it enables the users to understand the relationship between their emotional states and the recommendations. We recommend the researchers to improve this idea by 1) Extracting the movies to find the most used colors by the system. 2) Using more than two recommendation techniques to get the best capture of the movies. 3) Using more than three colors to find human emotions. 4) Design a new algorithm to solving the movie recommender system

VI. Acknowledgment

We take this opportunity to express our deep sense of gratitude to our project guide **Mr. John Kenny,** for his continuous guidance and encouragement throughout the duration of our major project work. It is because of his experience and wonderful knowledge; we can fulfill the requirement of completing the major project within the stipulated time. We would also like to thank **Dr. Jitendra Saturwar**, Head of the computer engineering department, and **Mrs. Vishakha Shelke, Mr.Chinmay Raut,** Project Coordinators for their encouragement, whole-hearted cooperation, and support.

We would also like to thank our Principal, **Dr. J. B. Patil**, and the management of Universal College of Engineering, Vasai, Mumbai for providing us with all the facilities and a work-friendly environment. We acknowledge with thanks, the assistance provided by departmental staff, library, and lab attendants.

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