DESIDOC Journal of Library & Information Technology, Vol. 28, No. 3, May 2008, pp. 17-35

Application Domain and Functional Classification of Recommender Systems—A Survey

K. Nageswara Rao

Defence Research & Development Laboratory
Kanchanbagh, Hyderabad- 500 058
E-mail:raokochi@hotmail.com

and

V.G. Talwar

University of Mysore, Mysore-570 005

ABSTRACT

The amount of scientific and technical information is growing exponentially. As a result, the scientific community has been overwhelmed by the information published in number of new books, journal articles, and conference proceedings. In addition to increasing number of publications, advances in information technology have dramatically reduced the barriers in electronic publishing and distribution of information over networks virtually anywhere in the world. As a result, the scientific community is facing the problem of locating relevant or interesting information. To address the problem of information overload and to sift all available information sources for useful information, recommender systems or filtering systems have emerged. Generally, recommender systems are used online to suggest items that users find interesting, thereby, benefiting both the user and merchant. Recommender systems benefit the user by making him suggestions on items that he is likely to purchase and the business by increase of sales. Filtering information or generation of recommendations by the recommender systems mimic the process of information retrieval systems by incorporating advanced profile building techniques, item/user representation techniques, filtering and recommendation techniques, and profile adaptation techniques. This paper addresses the application domain analysis, functional classification, advantages and disadvantages of various filtering and recommender systems.

Keywords: Recommender system, filtering system, domain analysis, content-based filtering system.

1. INTRODUCTION

Bibliographic control and information retrieval mechanisms were established and made available to the users in many libraries for identifying and locating relevant books, journal articles, reports, patents, etc. Ever increasing number of research scientists and dynamic research activities in multi-disciplinary subjects have resulted in the exponential growth of technical information and publication of large number of documents in the form of journal articles, conference proceedings, books, reports, standards, patents, etc. As more and more information became available electronically, the need for effective information retrieval and filtering tools became essential for easy access to relevant information. A poor information retrieval strategy results in retrieval of increased non-relevant documents.

A survey of biomedical journals conducted by K.S. Warren showed that the number of journals increases by 6-7 per cent every year, doubles every 10-15 years, and increases tenfold every 35-50 years. At the starting of the 19 century there were roughly

Received on 8 January 2008

1000 biomedical journals, 30 years ago there were 4,000 and 10 years ago 14,000 journals[1]. The history shows that scientific community has always found solution for the problem of information overload by preparing reviews for books and encyclopedias, indexes and abstracts for articles, and later computerised data banks. Explosive growth of information has resulted in the problem of information overload. Information overload is a perception that the information available is greater than can be managed effectively, and creates a degree of stress for which the coping strategies are ineffective. Richard Saul Wurman[2] explained the reasons of information overload in his book titled "*Information Anxiety*" as: when a person does not understand available information, feels overwhelmed by the amount of information to be understood, does not know if certain information exists, does not know how to find information and knows where to find information, but does not have the key to access it. So, continued efforts by experts in the field of information technology resulted in development of technological aids such as information retrieval systems, information filtering systems, intelligent agents, ranking algorithms, clustering techniques, categorisation techniques, data mining techniques, web mining techniques, personalisation and recommender systems to tackle the problem of information overload.

The advances in information and entertainment technologies have accelerated the availability of various alternative items in each and every domain, e.g. availability of hundreds of movies, television and music channels, books, restaurants, etc. In addition to this, the emergence of World Wide Web has opened up new possibilities for the users/customers to know the details/specifications of items seamlessly without visiting shops or outlets. It is an easy task for an individual to choose from limited number of available alternatives. When the collection becomes large, it is a tedious and time consuming task for any individual to really evaluate the features of items/products while purchasing quality, economic, and useful items. In such circumstances, people seek suggestions or recommendation from friends, relatives and experts who have knowledge about the items/products. The main purpose of the recommender systems is to provide tools to leverage the information hunting and gathering activities and interests of other people or groups of people. Recommendation systems have been an important application area and the focus of considerable recent academic and commercial interest. Generally, recommender systems are used online to suggest items that customers find interesting, thereby, benefiting both the customer and merchant. They benefit the customer by making him suggestions on items that he is likely to purchase and the business by increase of sales. In this paper, authors have surveyed, evaluated and classified recommender/filtering systems based on their functionality in various application domains.

2. APPLICATION DOMAIN ANALYSIS OF RECOMMENDER SYSTEMS

We have conducted literature survey to analyse various filtering and recommender systems falling under different application domains with brief introduction and purpose of the systems developed. The analysis revealed that some recommender systems are purely research prototypes, some are working on Internet and some systems provide their services for fee. All of the recommender/filtering systems were studied and analysed based on published technical literature in the form of technical reports, conference paper and journal articles. It is understood from the literature survey that majority of filtering/recommender systems were designed and developed for recommending Web pages, Netnews articles, personalised newspapers, music, movies, documents and information.

Research survey was conducted to study and classify approximately 96 filtering/recommender systems on various application domains. Out of 96 systems, 21 systems were developed in Web recommendation application domain, 12 systems in movie/TV recommendation application domain, 12 systems in information/document recommendation application domain, eight systems in Usenet news recommendation application domain, seven systems in information filtering and sharing domain, six systems in music recommendation domain, four systems in restaurant recommendation application domain, three systems in organisational expertise recommendation domain, three in personalised newspaper domain, three in e-Commerce application domain and software application domain, two systems each in travel recommendation application domain and two in electronic catalogue item recommendation. One system each fall under the recommender application domains such as learning resources recommendation, recommending interesting changes on Web, explanation-sharing recommendation, research grants recommendation, IT skills recommendation, similar user recommendation on P2P network, Web search and filtering, virtual fair recommendation, jokes recommendation, and image recommender system. Table 1 details various recommender systems and their application domain.

Table 1. Filtering/recommender systems and their application domain

Filtering/Recommender systems	Application domain
ACR News[3]	Usenet News Recommender System
Adaptive Place Advisor[4]	Restaurant Recommender System
Amalthaea[5,6]	Web Recommender System
Amazon.com[7]	Document/Information Recommender Systems
Anatagonomy[8]	Personalized Newspaper Recommender System
ARAS[9]	Information Products Recommender System
ArgueNet[10]	Web Recommender System
AVATAR[11]	Movie/TV Recommender System
Beehive[12]	Information Filtering and Sharing Systems
Bellcore Video Recommender[13]	Movie/TV Recommender System
Book Recommender System (BRS)[14]	Book Recommender System
CBCF[15]	Movie/TV Recommender System
CinemaScreen Recommender Agent[16]	Movie/TV Recommender System
CoCoA[17]	Music Recommender System
CoFIND[18]	Learning Resources Recommender System
Community Search Assistant[19]	Web Recommender System
DEMOIR[20]	Organizational Expertise Recommender System
Dietorecs[21]	Travel Recommender System
Do-I-Care[22,23]	Systems for Recommending Interesting Changes on Web
D-SIFTER[24]	Document/Information Recommender System
Eigentaste[25]	Online Jokes Recommender System
Entrée[26,27]	Restaurant Recommender System
Expertise Recommender[28]	Organizational Expertise Recommender System
ExplaNet[29]	Explanation Sharing Recommender System
Fab[30,31]	Web Recommender System
FAIRWIS[32]	Virtual Fair Recommender System
Flycasting[33]	Music Recommender System
Foafing the Music[34]	Music Recommender System
Foxtrot Recommender System[35]	Document/Information Recommender System
GroupLens[36,37]	Usenet News Recommender System
GroupMark[38]	Web Recommender System
IfWeb[39]	Web Recommender System
InfoFinder[40]	Document/Information Recommender System
INFOrmer[41]	Usenet News Recommender System
InfoScout[42]	Organizational Expertise Recommender System
InterestMap[43]	e-Commence Recommender System
INTIMATE[44]	Movie/TV Recommender System
Krakatoa Chronicle[45]	Personalized Newspaper Recommender System
LaboUr[46]	Research Grants Recommender System

Letizia[47]	Web Recommender System
Let's Browse[48]	Web Recommender System
LIBRA[49]	Document/Information Recommender System
LifestyleFinder[50]	Travel Recommender System
MetaLens[51,52]	e-Commence Recommender System
METIOREW[53]	Web Recommender System
MovieLens[54]	Movie/TV Recommender System
Movies2Go[55]	Movie/TV Recommender System
MyPYTHIA[56]	Software Recommender System
MyVU[57]	Information Products Recommender System
NAUTILUS[58]	Web Recommender System
News Dude[59]	Usenet News Recommender System
NewsWeeder[60]	Usenet News Recommender System
OWL[61]	IT Skills Recommender System
PEA[62]	Information Filtering and Sharing Systems
PEFNA[63]	Usenet News Recommender System
Personal WebWatcher[64]	Web Recommender System
pFilter[65]	Document/Information Recommender System
PHOAKS[66]	Web Recommender System
PILGRIM[67]	Web Recommender System
PipeCF[68]	Similar User Recommender System on P2P Network
Pocket RestaurantFinder[69]	Restaurant Recommender System
PocketLens[70,71]	Movie/TV Recommender System
PolyLens[72]	Restaurant Recommender System
PORSCHE[73]	Document/Information Recommender System
ProfBuilder[74]	Web Recommender System
PSUN[75]	Usenet News Recommender System
P-Tango[76]	Personalized Newspaper Recommender System
PYTHIA-II[77]	Software Recommender System
RAAP[78]	Web Recommender System
RACOFI[79]	Music Recommender System
Rama[80]	Information Filtering and Sharing Systems
RASCAL[81,82]	Software Recommender System
Re: Agent[83]	Information Filtering and Sharing Systems
Recommendation Explorer[84]	Movie/TV Recommender System
Recommender[85]	Movie/TV Recommender System
RecTree[86]	Movie/TV Recommender System
REFEREE[87]	Document/Information Recommender System
Ringo[88,89]	Music Recommender System
SELECT[90]	Document/Information Recommender System
SIFT Netnews[91]	Usenet News Recommender System

SiteIF[92]	Web Recommender System
SmartRadio[93,94]	Music Recommender System
SurlLen[95]	Web Recommender System
Syskill & Webert[96]	Web Recommender System
TalkMine[97]	Document/Information Recommender System
Tapestry[98]	Information Filtering and Sharing Systems
The MAUT Machine[99]	Electronic Catalog Item Recommender System
The Wasabi Personal Shopper[100]	Electronic Catalog Item Recommender System
TiVo[101]	Movie/TV Recommender System
VISCORS[102]	Image Recommender System
WebInEssence[103]	Document/Information Recommender System
WebMate[104]	Web Recommender System
WebSail[105,106]	Web Search and Filtering System
WebSell[107,108]	e-Commence Recommender System
WebSIFT[109]	Web Recommender System
WebWatcher[110,111]	Web Recommender System

3. FUNCTIONAL CLASSIFICATION OF RECOMMENDER SYSTEMS

Recommender systems can be classified broadly into six categories depending on the information they uses to recommend items. The systems, which use data about the items and information regarding the active user, are called "*Content-based Filtering Systems*". Other systems that do not use data about the content of the items but make recommendations to the active user using information about a set of users and their relation with the item, are called "*Collaborative Filtering Systems*". Systems that use demographic information such as age, gender, education, etc. of people for identifying types of users like a certain object and makes recommendations, are called "*Demographic Filtering Systems*". Another category of systems, which uses the functional knowledge to generate recommendations, i.e. knowledge about how a particular item meets a particular user need, and can reasoning about the relationship between a need and a product, are called "*Knowledge-based Recommender Systems*". The systems, which make suggestions based on computation of the utility of each object for the user, are called "*Utility-based Recommender Systems*". Recently, several authors proposed mixed approaches, attempting to keep the advantages of the combination of methods, and to reduce or take out disadvantages and problems. These systems are called "*Hybrid Recommender Systems*", which are the most interesting and can be considered as the state-of-the-art systems. The paper discusses four types of recommender systems based on their functionality.

3.1 Content-based Filtering/Recommender Systems

Content-based filtering systems recommend items based on descriptions or content of items rather than other user's ratings of the system. Instead of deriving a user-to-item correlation and defining methodologies, they use item-to-item correlation for generating recommendations. In these systems, the process of recommendation first starts by gathering content data about the items. For example, title, author, descriptors, etc. for the books or the director, cast, etc. for the movies are some of the common content information. Most of these systems use feature extraction techniques and information indexing to extract the content data. Generally, feature extraction can be achieved through various approaches which reduce the number of words, stop words, pruning, stemming, etc.[112]. In the next step, the user is asked to provide some ratings for the items randomly. Finally, the systems match un-rated books/items contents with the compiled user profile and assigns scores to the items depending on the match between user profile and item descriptions. The items are ranked according to their scores and presented to the user in order as output.

Consider the example in Table 2 to predict how recommendations are made for a particular user based on the relevance ratings provided by that user. It gives the relevance ratings for eight documents by four users. Users simply specify whether a particular document is relevant or not by mentioning 'Yes' as relevant and 'No' as non-relevant.

Table 2. Relevance ratings given by four users for eight documents

	Title of the document	User-1	User-2	User-3	User-4
D1	Mastering Data Mining: The Art and Science of Customer Relationship Management	Yes	No	No	?
D2	Discovering Knowledge in Data: An Introduction to Data Mining	Yes	No	No	?
D3	Datawarehousing and Data Mining: Implementing Strategic Knowledge Management	?	?	No	Yes
D4	Datawarehousing and Data Mining for Telecommunications	Yes	?	?	?
D5	Semiconductor Physics	No	No	Yes	No
D6	Physics of Semiconductor Devices	No	No	?	?
D7	Knowledge Management in Theory and Practice	No	Yes	?	?
D8	Knowledge Management for the Telecommunications Industry	No	Yes	No	?

In Table 2 User-1 has specified document D1, D2, D4 as relevant. The simplest form that the recommender system uses to recommend documents is through matching the content of rated document by the individual user. So, document D3 would be recommended to User-1 as title of the document has similarity with that of the rated documents. Likewise, D3 would be recommended to User-2, D6 would be recommended to User-3 and finally D1, D2, D4, D7 and D8 would be recommended to the User-4.

Content-based filtering systems have the following advantages:

- They don't require data on other users and are away from new user cold-start and sparsity problems
- These systems are capable of recommending items to users with unique tastes
- Can provide explanations of recommended items by explicitly listing content features or descriptions that caused an item to be recommended and
- Do not suffer from first-rater problem, i.e., they are capable of recommending new and unpopular items to each and every user.

The systems have the following drawbacks:

- The feature extraction and representation can be achieved automatically for machine parsable items such as news or papers. But human editors have to manually insert the features for items that are not machine parsable such as movies and songs. The activity of human involvement is highly subjective, expensive, time consuming and erroneous. Moreover, it is impossible to define right set of features for some sort of items such as jokes.
- Content-based filtering techniques have no inherent method for finding something unexpected and useful while searching for something else. The system recommends only more of what the user has already seen and indicated as "liking" the item. Hence, the user is restricted to see items similar to those already rated and these systems suffer from new-user cold start problem.
- In content-based filtering systems, items are limited to their initial descriptions or features. This limitation makes the content-based techniques dependent on the features that are specified explicitly.

3.2 Collaborative Filtering Systems

The term collaborative filtering was coined by Doug Terry at Xerox PARC in the early nineties. In its initial conception, collaborative filtering referred to methods for information filtering based on the preferences expressed by people about items or documents. Due to the generality of this definition, a variety of methods, models, and technologies have emerged in the past decade that all claim to address the problem of collaborative filtering. A pure collaborative filtering system is one which does no analysis of the items at all—in fact, all that is known about an item is a unique identifier[30]. The first recommender that used a collaborative approach was GroupLens[37], which presented the so-called neighborhood based approach. Other approaches were proposed, using Bayesian networks, singular value decomposition with neural networks classification and induction rule learning[113].

The goal of collaborative filtering systems is to suggest new items or predict the utility of a certain item for a particular user based on users past liking and the opinions of other like-minded users. It is widely used and perhaps the most familiar recommendation technique implemented in several e-Commerce applications. In general, collaborative filtering systems collect the ratings for a list of items from a list of users. Opinions can be explicitly given by the user as a rating score or can be implicitly derived from the historical data of the user. When the user does not the rate a particular item, there is the possibility of having a null set. The correlation between the user seeking recommendations and other users are computed and neighbours or peer groups are created using different correlation methods. Finally, predictions or recommendations for the items that the user has not rated but the neighbours have rated are computed and presented to the user in decreasing order of preference. It is important to note that collaborative filtering systems use the nearest neighbour model and rely upon the assumption that people who agreed in the past are likely to agree in the future[37].

Consider the example in Table 3 to predict how recommendations are made for a particular user. It shows the ratings for seven documents by six users. Users specify how relevant a particular document with the help of 1-5 ratings scale, i.e. 1 representing low relevant and 5 representing highly relevant.

The simplest way of predicting the ratings that User-X would give to Doc-6 or to recommend documents to the User-X based on his ratings to other documents, it would be reasonable to consider users that have similar pattern of ratings with User-X. In this example, User-2 has rated Doc-2, Doc-4, and Doc-5 with same or similar ratings as that of User-X. Hence, Doc-6 is recommended to the User-X or the predicted rating for Doc-6 by the User-X is 2.

Another approach would be to find the degree of correlation between User-X and other users. Rather than relying on just the most similar user with similar ratings as explained above, a weighted average of the recommendations of several users can be found. In such circumstances the weightage to user's rating would be found by degree of correlation between the two users. The most common measure of correlation is the Pearson Product Moment Correlation (called Pearson's correlation for short). When computed in a sample, it is designated by the letter "*r*" and is sometimes called "*Pearson's r*". Pearson's correlation reflects the degree of linear relationship between two variables. It ranges from +1 to -1. A correlation of +1 means that there is a perfect positive linear relationship between variables.

The correlation coefficient of a set of observations $\{(x_i, y_i) : i = 1,2,3...n\}$ is given by the formula:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

In collaborative filtering systems all users may not rate all documents. Here, for the purpose of calculation, zero value has been given for non-rated documents. From the above sample data, the Pearson correlation coefficient between User-X and User-1 for all the document collection is 0.975, User-X and User-2 is 0.996, User-X and User-3 is 0.933, User-X and User-4 is 0.992 and User-X and User-5 is 0.982, respectively. Mathematically, it is clear that the correlation between User-X and User-2 is more. Hence, collaborative filtering system recommends Doc-6 to User-X as User-2 is more similar and has rated Doc-6.

Table 3. Ratings of six users for seven documents

	Doc-1	Doc-2	Doc-3	Doc-4	Doc-5	Doc-6	Doc-7
User-1	1	3	0	1	0	0	2
User-2	0	1	0	4	0	2	5
User-3	5	0	1	0	4	5	0
User-4	0	1	0	3	0	2	3
User-5	0	2	0	4	0	1	1
User-X	0	1	0	4	0	?	5

Collaborative filtering systems have the following advantages:

- They do not need a representation of items in terms of features i.e. genre and actor of the movie, title and author of the book, but it is based only on the judgment of participating user community. Hence, collaborative filtering can be applied to virtually any kind of item, i.e., papers, news, websites, movies, songs, books, jokes, etc.
- Scalability of the items database can be large since the technique does not require any human involvement for tagging descriptions or features
- They can cope with cross-genre recommendations such as making confident predictions of entirely different items to the user who have never rated such items in the past
- They do not require domain-knowledge for tagging the features to the items, therefore, it is a time saving activity
- The quality of the recommendations would be improved over time.

Collaborative filtering systems have the following disadvantages:

- Cold Start or First Raster Problem: When new item is added to the database, the item can not be recommended to any user until the item is either rated by another user(s) or correlated with other similar items of the database[114,115,116].
- Data Sparseness Problem: Most of the e-Commerce applications contains millions of users and millions of items. In practice even active users only rate a few of the entire set of items and results in a very sparse matrix in collaborative filtering. The sparseness of a collaborative filtering matrix is the percentage of empty cells. Because of the presence of empty cells, collaborative filtering systems may not locate successful neighbours and generate weak recommendations.
- Critical Mass Problem: For the recommendations to be reliable, the filtering system needs a very large number of people (typically thousands) to express their preferences about a relatively large number of options (typically dozens). But developing such a database for achieving a critical mass of participants makes collaborative filtering experiments so expensive and time consuming, because users will not be very motivated to express preferences in the beginning stages when the system cannot yet help them.
- Unusual User Problem: In a small or medium community of users, there are individuals whose opinions or tastes are unusual. It means that an individual do not agree or disagree consistently with any of existing group of people. So, these individuals rarely receive accurate collaborative recommendations even when the critical mass of users is achieved.
- Popularity Bias: Collaborative filtering systems cannot recommend items to someone with unique tastes, but tends to recommend popular items.

3.3 Demographic Filtering Systems

A general technique people use to build models of other people very quickly is the evocation of stereotypes or clusters of characteristics. A stereotype is a collection of frequently occurring characteristics of users. For example, one might guess that if someone is a judge, he or she is probably over forty, well educated, reasonably pro-establishment, fairly affluent, honest, and well-respected in the community. Although not all of these attributes are necessarily true for any particular judge, a person would tend to assume them until explicitly shown otherwise. Therefore, a stereotype normally contains the common knowledge about a group of users. When a new user enters the system, he will be assigned into related stereotype(s) if some of his characteristics match that of a particular stereotype(s). The same concept is used in demographic recommender systems by the use of descriptions of people to learn the relationships between a single item and the class or type of people who liked it. Demographic-based recommender systems use prior knowledge on demographic information about the users and their opinions for the recommended items as basis for recommendations. Demographic systems are stereotypical, because they depend on the assumption that all users belonging to a certain demographic group have similar taste or preference[117].

A demographic recommender system, Grundy, was one of the first book recommender system developed by Elaine Rich[118]. Grundy bunds models of its users, with the aid of stereotypes, and then exploits those models to guide it in its task, suggesting novels that people may find interesting. Users enter keywords describing their personality, not their information need in order to create a user profile. Grundy then associates terms used in the users' self-descriptions with pre-defined stereotypes. These stereotypes expand into attribute rating pairs describing the users' information needs that are aggregated to form the object ratings when making predictions.

Another recommender system is the LifeStyle Finder[40], which suggests items and webpages to users. It attempts to identify one of pre-existing clusters of demographic groups to which a user belongs and tailors recommendations to users based on information about others in that cluster. Demographic techniques attempt to form "people-to-people" correlations like collaborative filtering, but uses different data.

M.J. Pazzani[119] attempted to find regularities among users, by applying on them Winnow algorithm—an algorithm originally designed for text classification. User profiles utilised for similarity calculations had the form of user demographic vectors.

Demographic filtering systems have the following advantages:

- The advantage of a demographic approach is that it does not require a history of user ratings of the type required by collaborative and content-based techniques
- Demographic approach is quick and straightforward method for making assumptions based on limited observations, and
- Demographic filtering systems could be implemented quickly and easily.

Demographic filtering systems have the following disadvantages:

- For the demographic filtering to be effective, it is necessary to collect complete demographic information about users. In practice, it is difficult to collect such information as it involves privacy issues
- Demographic filtering systems suffer from both new-user cold-start problem and new-item cold-start problem
- The formation of demographic clusters is based on a generalisation of the user's interests. So, demographic systems try to recommend the same item to people with similar demographic profiles and the recommendations are too general.

3.4 Hybrid Recommender Systems

Several recommender systems use a hybrid approach by combining content-based and collaborative methods to avoid certain limitations and disadvantages of content-based and collaborative systems. Different filtering/recommender systems and type of filtering techniques used for producing recommendations or predictions have been shown in *Appendix 1*.

4. CONCLUSION

Queries in information retrieval play an important role in searching and retrieving relevant information from static collection of documents. But in the case of information filtering/recommender systems, profiles play an important role to filter relevant information from dynamic stream of incoming data. Every recommender system needs some sort of input collected explicitly or implicitly to generate recommendations. Using this input, the recommender system builds user profile which represents any of the IR/profile representation models viz., vector space model, semantic networks, weighted n-grams, associative networks etc.

The recommender system matches the user profile with the descriptions of items or users with similar taste to recommend items of interest to the user. There are three matching techniques generally used by the recommender systems such as: content-based filtering, collaborative filtering, demographic filtering or hybrid technique. Finally, these systems provide Top-N recommendations followed by fine tuning the user profile with the help of relevance feedback mechanism to retrieve more relevant items. All these 96 systems under study have their advantages and disadvantages in the process of recommending items to the targeted users. Hybrid recommender systems are more important and they are going to play vital role in the next-generation of recommender systems, because they minimize the disadvantages and maximize the utility of content-based filtering systems and collaborative filtering systems.

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About the Author

Shri K. Nageswara Rao received Masters degree in Physics in 1988 from Sri Venkateswara University, Tirupati, and Masters degree in Library and Information Science in 1992 from Annamalai University. From 1993 to 1995, he worked at the National Informatics Centre, Hyderabad. During 1995 to 1999, he worked as scientist at the Naval Physical and Oceanographic Laboratory, Kochi. Presently, he is Head, Technical Information Centre, Defence Reseach and Development Laboratory, Hyderabad. His research interest encompass Internet technologies, web mining, design and development of digital libraries, and recommender systems. He has published/presented a number of technical papers in national/international journals/conferences.

Filtering/recommender systems and type of filtering techniques used for producing recommendations

Filtering/Recommender system	CBF	CF	HF	Others
ACR News	X			
Adaptive Place Advisor	X			
Amalthaea	X			
Amazon.com			X	
Anatagonomy			X	
ARAS	X			
ArgueNet	X			
AVATAR			X	
Beehive		X		
Bellcore Video Recommender		X		
Book Recommender System (BRS)	X			
CBCF			X	
CinemaScreen Recommender Agent			X	
CoCoA		X		Case-based Reasoning
CoFIND		X		
Community Search Assistant		X		
DEMOIR		X		
Dietorecs				Case-based Reasoning
Do-I-Care		X		
D-SIFTER		X		
Eigentaste		X		
Entrée		X		
Expertise Recommender		X		
ExplaNet		X		
Fab			X	
FAIRWIS		X		
Flycasting		X		
Foafing the Music	X			
Foxtrot Recommender System			X	
GroupLens		X		
GroupMark			X	
ifWeb	X			
InfoFinder	X			
INFOrmer	X			
InfoScout		X		
InterestMap		X		
INTIMATE	X			
Krakatoa Chronicle			X	
LaboUr			X	

Letizia	X		
Let's Browse	X		
LIBRA	X		
LifestyleFinder			Demographic Filtering
MetaLens			X
METIOREW			X
MovieLens			X
Movies2Go	X		
MyPYTHIA	X		
MyVU	X		
NAUTILUS	X		
News Dude	X		
NewsWeeder			X
OWL		X	
PEA	X		
PEFNA	X		
Personal WebWatcher	X		
pFilter	X		
PHOAKS		X	
PILGRIM		X	
PipeCF		X	
Pocket RestaurantFinder	X		
PocketLens		X	
PolyLens		X	
PORSCHE		X	
ProfBuilder			X
PSUN	X		
P-Tango			X
PYTHIA-II	X		
RAAP			X
RACOFI		X	
Rama	X		
RASCAL		X	
Re: Agent	X		
Recommendation Explorer	X		
Recommender			X
RecTree		X	
REFEREE			X
Ringo		X	
SELECT			X
SIFT Netnews	X		

SiteIF	X			
SmartRadio		X		
SurlLen		X		
Syskill & Webert	X			
TalkMine			X	
Tapestry		X		
The MAUT Machine	X			
The Wasabi Personal Shopper				Case-based Reasoning
TiVo		X		
VISCORS			X	
WebInEssence	X			
WebMate	X			
WebSail			X	
WebSell			X	
WebSIFT			X	
WebWatcher			X	

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DESIDOC Journal of Library & Information Technology
House Bulletin Group
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Metcalfe House, Delhi-110 054
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