Review of Recommender Systems and Their Applications

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Abstract—**In the past few decades, the concepts of personalization in the forms of recommender system, information filtering, or customization are not only quickly becoming more accepted by the public, but is also drawing considerable attention from enterprises. Therefore, a number of studies based on personalized recommendations have subsequently been produced. Most of these studies apply to E-commerce, website, and information, and some apply to teaching, tourism, and TV programs. Because of the recent rise of Web 3.0 and emphasis on providing more complete personal information and service through an efficient method, the recommender application has gradually developed towards mobile commerce, mobile information, or social network. Many studies have adopted Content-Based (CB), Collaborative Filtering (CF), and the hybrid approach as the main recommender style in the analysis. There are few or even no studies that have emphasized on the review of recommendations. For this reason, this study aims to collect, analyze, and review the research topics of recommender systems and their application in the past few decades. This study collects the research types from various researchers. The literature arrangement of this study can help researchers to understand the recommender system researches in a clear sense and in a short time.**

Keywords— **Recommender System, Recommender Technique, Information Filtering, Personalization,**

1. INTRODUCTION

In the past few decades, the rapid development of the internet, information technology, and digital information makes knowledge has grown abundantly [119], but this also has caused information overload in recent years [176]. However, people tend to be confused because of the great deal of information. Today, information is easy to search and obtain. But can people get the information they really want during the search process? For example, customers often need to spend much time on finding suitable products from a variety of products; readers also need to browse through many different types of articles before discovering the ones they are interested in. Enterprises can't provide suitable products or services because they can't understand customers' behavior or preference, therefore, they may lose the source of the customers or reduce customer loyalty [153,154,169]. Both users and enterprises need to spend considerable time and devote more efforts to acquire the things they need. Besides, it is very important to search information efficiently. As a result, many researchers start to take personalization or customization into consideration to screen and filter the massive information. In this way, users or enterprises can find information they are interested in within the shortest time and at a minimum costs.

People desire appropriate knowledge in this information era. Their requirement for information acquisition differs from the past. They expect to get the information they need within the shortest time. Based on this demand, many techniques are proposed to fulfill this requirement. One of them is the Information Retrieval (IR) [29,32,46,83,109,152,157]. IR can execute user commands (such as keyword), find out the information or document from a massive database to match user demand and return the results back to users. One is the famous search engine, Google [9]; however, the returning of user results includes too much irrelevant information. Consequently, users must spend time to screen information one by one in order to find out their required information. The most distinctive characteristic of information retrieval is that users must initiate information request to play its role. Nonetheless, not all users can initiate information request very often; indeed, users expect to passively receive information provided. Hence, one other technique called Information Filtering (IF) [46,83,103,129,152,155,176], is proposed for complementing the shortcomings of information retrieval. Information filtering is another effective tool for mitigating information overload. Its principle of operation is based on analyzing user behavior to acquire their preferences or interests and thereby filter or screen out information they need. The difference between IF and IR is that information retrieval must passively wait for query command from users before proceeding further; in contrast, information filtering can actively assist users to find the relevant information they are interested in.

The earliest concept of personalization was introduced in the manufacturing industry. Actually, its name was usually called Mass-Customization [153] in the early literature. With advances in technology, manufacturing cost reduces, and cost is no longer the only consideration. Therefore, the industry introduced the concept of customization to apply in the service industry and to improve the service quality. Some researchers called this type of service as customization or personalization [104,140].

Personalization is a concept of customization according to personal preferences. For example, Amazon.com recommends registered members with relevant books and CDs according to their preference [76,120]. For social networks with emphasis on member service, the technique of personalization gives them the opportunity and capability to understand customers' preferences in order to provide personalized services. In other words, personalization puts emphasis on understanding customer's characteristics and grasping the real needs of the customer. Indeed, the customer's satisfaction comes from the gap between expectation and real situations; therefore, how to minimize the gap is an important task for an enterprise. Weng et al. [175] proposed the process of establishing the personalization from bottom-up (see figure 1). To actively provide customers with information or preference commodity, customer responses are measured to give feedback to other steps, and personal requirements are analyzed and recorded.

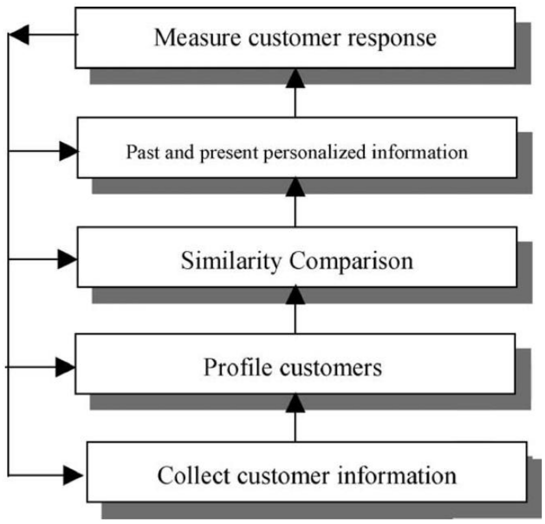


Fig. 1 Process of Personalization [175]

As long as no privacy has been affected, personalized service is the key to attract customers. In order to provide expected products [100], raise service quality, and customer satisfaction, customer profiles including preferences, historical transaction data, purchasing behavior, etc., are analyzed. If an enterprise adopts such concept and increases relevant service strategy, the enterprise will not only maintain existing customers but also attract new customers. In this way, enterprises will increase potential revenue.

The concept of personalization provides with personalized products and information, and has been widely applied as the service of recommendation. Many online information services, such as Amazon, Yahoo, CDNow, eBay, ZDNet, Uniqlo, Fender, and so on [28,84,153], also incorporate the recommender systems for personalization's service. Indeed, with the popularity of mobile service and the promotion of the cloud environment, recommender systems have become very important, because of the ability of providing information filtering, personalization, and satisfy the customer's preferences.

As customer-oriented concept gains more emphasis, enterprises gradually place more attention on a recommender system. To provide more methods, technique, or systems to cope with enterprise's desire, many researchers have studied the application of recommender systems. We have reviewed these literatures with a total of 133 papers as shown in Table 1. From Table 1, we can see that researches on the application domain related to "information" the most prevalent which takes up 50% over 133 papers. Also, we notice that commerce such as E-commerce, M-commerce, and B2B commerce also apply the recommender system. As far as the degree of research focus is concerned, the quantity of the information research is more than commerce. In our study, we found that the blog and mobile commerce has not appeared in the application of recommendation system until the recent years.

TABLE 1
RECOMMENDER SYSTEM APPLICATION DOMAINS

Application domain	References Number
blog	[57,101,167]
book	[129]
document	[49,81,92,105,152,172,173, 181]
E-commerce	[1,5,12,23,28,30,34,36,37,38, 39,41,47,55,60,64,71,72,73, 79,80,82,85,86, 98,104,108, 118,122, 136,146,147,153, 159,169,170,175,183,184]
learning	[18,65,66,134,165]
Industry	[113,163]
forum	[143]
information	[3,35,45,48,50,51,83,109,110,116,132,135,155,166,188]
manufacturing enterprise	[186]
Mobile commerce	[21,63,91,94,99,179,180]
movie	[2,4,13,16,24,102,120,121,133, 139,149,164,174,176]
music	[9,25,26,42,103,114,140,157]
news	[33,40,54,75,87]
Soft project planning	[168]
tag	[185]
teaching	[67,68]
tourism	[76]
TV-program	[53,189]
virtual community	[97]
Web	[14,56,70,78,84,95,96,111, 112,115,125,131,151,171,182]
workflow	[187]

This research also organizes all these reviewed papers to create Figure 2 to illustrate the application research categories of recommender system. From Figure 2, we can see that the research application aspects based on recommendation concept are very extensive, and include commerce, information, Web-service, industry, and education, and they are all in the research focus. Because of the prosperity of the E-commerce market, researches on E-commerce appeared rapidly after 2000. In order to expand customers and business opportunities, enterprises utilize recommender system to provide personalized products or services. Enterprises also utilize recommender system to attract the potential customers and increase their willingness to purchase products or services. Thus, many enterprises consider a recommender system as indispensable marketing strategy. Right now, books, articles, music, movies, news, and television programs can be introduced with personalized service by utilizing a recommender system.

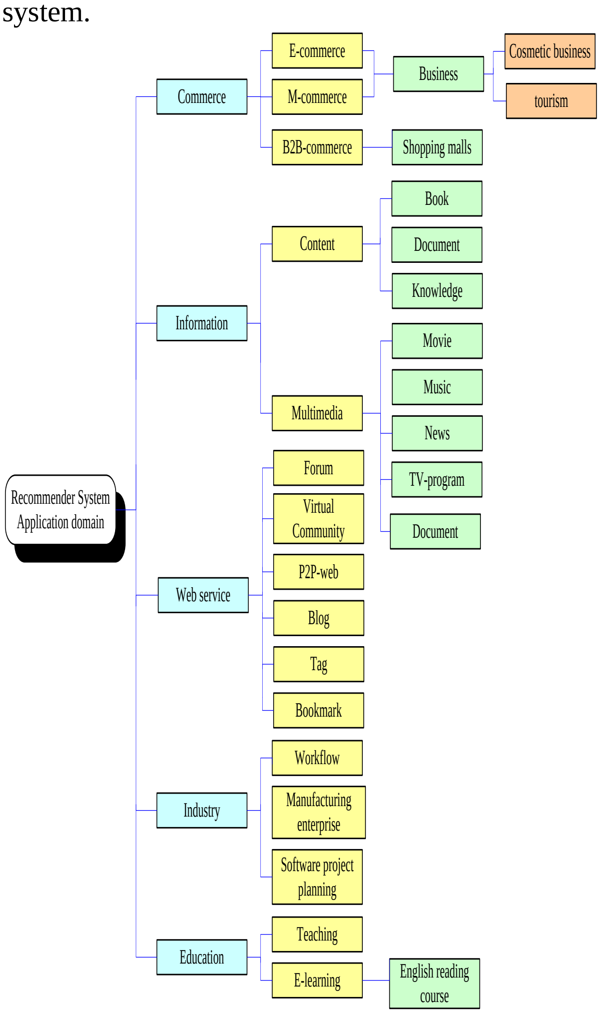
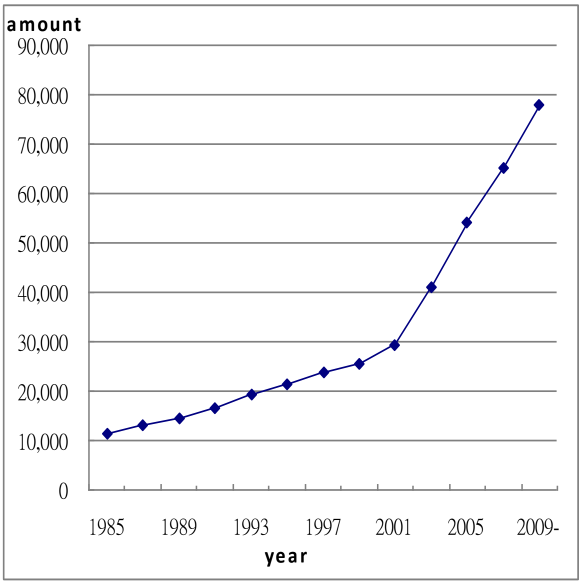


Fig. 2 Recommender System Application Domain Base on The Reviewed Literature

To investigate the research trend and research quantity of recommender system, we select SDOL, one of the most important literature databases in science and technology, to understand the research growth from 1824 to

September 2010. From SDOL database, it shows that between 1834 and September 2010, we found topics or relevant contents including 486,556 papers, if we set the search keywords as followings: "recommendation," "recommender," "recommender systems," "recommender system," "recommendation system," "recommending," "recommendations," "collaborative filtering," "content-based," "personalized recommender system", "hybrid recommender systems," "collaborative filters". We further discovered that nearly 84.5% of research appeared after 1985 (as shown in Figure 3). We can see from Figure 3, the amount of recommender researches grown rapidly 2001. This means that the applications of recommender system gains researchers attention and has become an important research domain. However, the majority of the studies focus on the application aspect. There are few studies of the various recommender types.



(a)

Year	Papers amount
1985	11255
1989	14369
1993	19201
1997	23678
2001	29238
2005	54044
2009-	77796

(b)

Fig. 3 Research Quantity on Recommender Domain (a) The plot (b) The figures

In our review study, we also collect some papers that had reviewed on the recommender system. Qu et al. (2000) [141], reviewed the algorithms of building the recommender system, but this review did not cover the current trend such as M-commerce, Tags, and Blogs and so on, and they didn't mention the new techniques and classification defects of recommendation system. Schafer et al. (1999) [153] only focused on the application area of E-commerce, and merely introduced the application system of E-commerce and brief technique classification. In Chesani's research (2002) [32], he discussed the recommendation system proposed, therefore, the application area of recommendation system did not introduce in this research. In the research of Montaner et al. (2003) [128] the content of their research emphasized on the technique of recommendation. Although they provide comparable tables of data items, the explanations of the content were brief.

This research focuses on the application domain of recommender system that did not study in the past by any other researcher. Hence, it is our goal that this research is to achieve the followings.

1. Help researchers understand the origin and evolution of recommendation system in a systematical way.
2. Provide the classification, usage, and type of recommendation system application area for better research.
3. Explain types of problem generated by various types of recommendation systems.
4. Inspire researchers with the improvement and application of recommender systems.
5. Help researchers understand the trend of application hereafter.

2. RECOMMENDATION SYSTEMS

In this section, we will describe the recommendation system's origin, and the procedures of recommender systems.

2.1. Origin of Recommendation

What does recommendation mean? In general, when people cannot make a decision for the things they are interested in, they usually consult with family or friends who have similar experiences. They will make the final decision if positive replies can be obtained, and there is the meaning of "recommendation" in this decision-making process. Another example is watching a movie. People often refer to the movie critique, the box office records, or the comments of others who have seen the movie. If such information provides positive evaluation or recommendation, people will show more intention to watch the movie. There are many similar situations in life such as music, food, shopping, not to mention the online shopping. There are various products and information when you open the website of E-commerce, and it often takes considerable time to select products or services for better service. Amazon, for example, initiated the technology service strategy that can recommend the appropriate books according to the reading habits or purchasing records of customers. Indeed, expert recommendation other customer's recommendation, bestselling items, personalized recommendation, and even cross-selling information are useful data for recommendation [76,154].

Often, a situation may happen that one may take action if one believes in positive Word-Of-Mouth (WOM) publicity, with regret. In other words, popular style does not always match personal taste. For example, bestselling novels are not necessarily a reader's favorite books. Therefore, we need to take customer preference into consideration after understanding the evaluation or publicity [133]. It is clear that a good recommendation is to provide sufficient information and to understand customers' preference for finding what they want.

The term, "recommendation" can also refer to the degree of information filtering to produce the topics or contents users are interested in [133]. Nonetheless, "personalization" also emphasizes meeting personal requirement or interests after information filtering for individual users [76]. Therefore, a recommendation, in essence, is usually as important as personalized recommendation. The main purpose of recommendation aims to timely provide suitable and valuable information according to user demand, and such information will be used as reference for supplementing decision-making.

According to our study based on the SDOL database, research on "recommendation" started in 1823, and the follow-up studies rapidly proposed one after another, leading to a highly considerable growth after 1985. Research issues also become diverse as shown in Table 2. There are also recommendation issues of commerce, information, Web service, Industry, Education. After 2005, there is a rise of research areas such as mobile commerce, concept of Web 3.0, cloud service, social network, etc.

2.2. The So-called Recommender System

In general, recommender system refers to the specification of a recommender concept. With the massive information, a recommendation system can introduce users to choose the useful information they interested with personalized service. To rapidly and precisely provide information, the most common method used in recommender system is to build up a user profile that can be collected through the questionnaire, the purchasing products, or the records of website browsing or transaction history. Usually a recommender system will incorporate the information filtering process to filter out content related to users and then compile, classify, remark, or establish an index. In this way, it is convenient to judge the connection between the data from database and user profile. Recommender system can help users filter out the useful information or find out the similar groups in order to recommend products or services meeting user expectations.

In the recommender study of Goldberg et al. [49], a collaborative filtering method was used to filter out the information that is useful to users. Goldberg et al. also proposed the famous recommender system, Tapestry, which is a type of information filtering recommender system [156,177]. Resnick and Varian [144] argued that in addition to filtering information, a recommender should also emphasize giving the information that the users are interested in.

The early recommender system was an information filtering system whose primary tasks was filtering. The common information filtering system can also be referred to as a recommender system for the following two reasons.

(1) Recommender and customer do not have a mutual understanding and the recommender system does not need to know the customer.
(2) The term "recommendation" contains the meaning of emphasizing a user's interested items in addition to filtering out unnecessary information, so recommendation meets the system philosophy more.

Therefore, a recommender system analyzes user preferences, interests, and behaviors and generates the potential information, the service, or the products needed by users. Besides, if enterprises arrange recommender systems into their framework, they will get more potential benefits. For example, businesses may obtain the customers' prior purchasing or browsing records through recommender system, and analyze or judge the customers' preference behaviors as reference for recommender prediction. In this way, it cannot only stimulate customers to consume but also increase the opportunity of marketing commodities. [28,84,175].

Rashid et al. [142] once defined a recommender system thus: A decision-making strategy for users under a complex information environment. It could also generate a recommended list to users according to the understanding of users and items. Martin-Guerrero et al. [115] suggested that recommender systems could increase the complexity of user browsing. It implies that users may stay longer on the sites and be more willing to purchase the products. Schafer et al. [153] defined a recommender system from the perspective of E-commerce. He believed that recommender system guides users through the records of knowledge that is related to user preferences and products. Many cases have successfully introduced recommender system to E-commerce websites, including: Amazon.com, CDNow.com, Levis.com, Drugstore.com, MovieFinder.com, Reel.com, and many other famous sites [28,117,139,154] as shown in Table 2.

TABLE 2
WELL-KNOWN COMPANIES THAT USE RECOMMENDER SYSTEM

Company	Recommender Products
Launch.com	Online Music
Amazon.com	Books,CD etc.
Moviefinder.com	Movie
MovieLens	Movie
Drugstore.com	Drugstore
CDNOW	music
IMDb	movie
Barnes & NOBLE	Books, Movies, Music, Toy, Games etc.

2.3. Procedures of Recommender Systems

In general, the procedures for recommender systems contain the following three procedures (as shown in Figure 4). First, collect the relevant information of users and establish customers' database. Second, recommend according to customers' database. Finally, allow users to evaluate the recommendation results and give feedback to the system for adjustment.

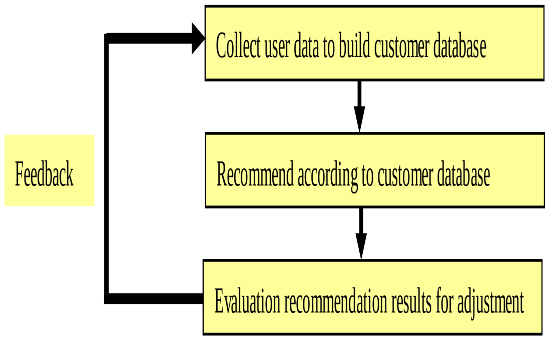


Fig. 4 Procedures of Recommender Systems

Usually users must provide appropriate feedback [17,62] in the process of recommendation to maintain the recommendation effectiveness of recommender system. In this way, a recommender system can reflect the personal interests or the degree of preference. Adjustment will be made according to user preferences and user preference data will be modified to filter out most of these uninterested items in the next recommendation [83,155]. Recommendations generated by the system provide appropriate evaluation according to the degree of personal preference, known as relevance feedback [109,160,161]. Goldberg et al. [49] even divided such feedback type into two categories for collecting user interests, i.e., explicit feedback and implicit feedback：

(1) Explicit Feedback [32,42,58,72,77,93, 98,128, 148]: The user expresses the degree of preference through the evaluation of information or product items. Through the feedback of appropriate evaluation information, the system can precisely understand the information of user preference or use such information for correcting user preference information [61]. Since the information given from a user is reliable, therefore, the system can generate more accurate recommendation results. Nonetheless, users may give the evaluation on preferred items only, and it sometimes will cause the user additional burden.

(2) Implicit Feedback [32,42,58,72,93, 98,128, 132,148]: Implicit feedback is important for the less interactive or casual user [59]. The system determines user preference or the changing situations of preferred items through user behavior and selected items. The

system may acquire user information according to the user browsing information such as number of clicks and stay time, and the records of purchase as the source of recommendation adjustment. The user does not need to provide the preference information, and the system will effectively recommend to user.

The biggest difference between explicit feedback and implicit feedback lies on the degree of mutual interaction between the user and the system. The higher the degree of interaction, the more the actual preference of user information will be reflected. However, explicit feedback needs the user to respond the information; therefore, reducing the user feedback burden is the key consideration in the current design of recommender system. The following table compares the strengths and weaknesses between explicit and implicit feedback (see Table 3).

TABLE 3
COMPARISON BETWEEN EXPLICIT AND IMPLICIT FEEDBACKS

	Explicit feedback	Implicit feedback
Data Amount	Few	Many
Strength	Direct and accurate data	Less burden on users
Weakness	➢ Burden for users ➢Evaluation Scarcity Issue	➢Doubt on the correctness of data ➢Long computing time ➢High acquisition costs
Improvement	➢ Improve evaluation interface ➢Provide evaluation feedback	➢ Improve calculation algorithm ➢ Raise the data correctness

3. CLASSIFICATION OF RECOMMENDER SYSTEM

Recommender system provides the most relevant and precise recommended items to user according to user preference. Schafer et al. [153] introduced common recommender types into four categories in accordance with the application of recommender system:

(1) Non-Personalized Recommendations [28]:
Recommendation is made based on the average item preference of other users. This type of recommendation will not independently recommend according to the personal preference. Therefore, all users receive the same product recommendation without personalized characteristics, and all users receive the identical items of recommendation.

(2) Attribute-Based Recommendations:
Recommendation is made based on attributes and characteristics of items. The main emphasis lies on analyzing the characteristics of item attributes that must be representative and specific. Therefore, the attribute-based recommendation is also known as Content-Based (CB) approach.

(3) Item-to-Item Correlation Recommendations:
Recommendation is made according to the correlation between item and item selected by users. In the example of news recommendation, a user wants to search for the news title in the news category with preference. The system will find out the related news titles mostly read by other users and recommend to this user in order to increase the news quantity.

(4)People-to-People Correlation Recommendations: Recommendation is made according to the past browsing and the purchasing behavior of similar users to find out their similar behaviors. Such technique is often referred to as Collaborative Filtering (CF) recommendation that is originated from Information Filtering (IF) technique. This technique mainly recommends information base on the group of similar preference.

Besides the above four types of recommender system, there are two techniques are commonly applied in many researches, i.e., CB and CF [43-1,25,122]. Also, there is another category in most literatures, i.e., the Hybrid recommendation [5,19,22,26,28,37,43-1,50,70,72,102,103]. CB accomplishes recommendation by analyzing user preferences through the historical records of using. CF refers to the collaborative recommendation through other user evaluations. Hybrid recommendation not only contains the advantages of the above two types but also has better recommended quality in comparison with the individual model of CB and CF. From our review study, we had organized and classified the recommender systems base on the method being applied (see Table 4-1 ~ Table 4-3).

TABLE 4-1
CONTENT-BASED RECOMMENDER SYSTEM AND THEIR APPLICATION FIELDS (SOURCE：[128] & THIS RESEARCH)

SYSTEM NAME	DOMAIN	References Number
ACR News	Netnews filtering	[126]
Amalthaea	Web recommender	[130]
IfWeb	Web recommender	[10,123]
InfoFinder	Information recommender	[89,90]
INFOrmer	Netnews filtering	[145,160]
Let's Browse	Web recommender	[107]
Letizia	Web recommender	[106]
News Dude	Netnews recommender	[17]
NewT	Netnews filtering	[158]
PSUN	Netnews recommender	[161]
Re:Agent	E-mail filtering	[19]
SIFT Netnews	Netnews filtering	[177]
SiteIF	Web recommender	[162]
Syskill & Webert	Web recommender	[137,138]
Webmate	Web recommender	[27]
WebSail	Web search filtering	[31]

TABLE 4-2
COLLABORATIVE FILTERING RECOMMENDER SYSTEM AND THEIR APPLICATION FIELDS (SOURCE：[128] & THIS RESEARCH)

SYSTEM NAME	DOMAIN	References Number
Adaptive Radio	Music recommender	[82]
Beehive	Sharing news	[69]
Bellcore Video Recom	Movie recommender	[62]
Flytrap	Music recommender	[82]
GroupLens	Netnews recommender	[51,87,121, 143,156]
Lotus notes	News or articles recommender	[141]
MusicFX	Music recommender	[82]
Pocket RestaurantFinder	Restaurant recommender	[82]
PolyLens	Movie recommender	[133]
RACOFI	Music recommender	[9]
Ringo/FireFly	Music recommender	[137,149, 156]
Smart Radio	Music lists recommender	[58,59]
Tapestry	E-mail filtering	[49,141, 156,177]
TV4M	TV programs recommender	[82]

TABLE 4-3
HYBRID RECOMMENDER SYSTEM AND THEIR APPLICATION FIELDS (SOURCE：[128] & THIS RESEARCH)

SYSTEM NAME	DOMAIN	References Number
Amazon	E-commerce	[7]
Anatagonomy	Personalized newspaper	[148]
Casmir	Document recommender	[15]
CDNow	E-commerce	[7]
Fab	Web, News, and Document recommender	[11,49]
INFOS	News recommender	[127]
Jester	Jokes recommender	[8]
Krakatoa Chronicle	Personalized newspaper	[77]
LifeStyle Finder	Purchase, travel, and store recommender	[88]
MovieLens	Movie recommender	[52,133]
NewsWeeder	Netnews recommender	[93]
Personal WebWatcher	Web recommender	[124]
RAAP	Web recommender	[44]
Recommender	Movie recommender	[13]
WebSell	Purchase recommender	[43]
WebSift	Web recommender	[41]
WebWatcher	Web recommender	[9,74]

3.1. Content-based (CB) Recommendations

CB recommendations refer to recommending customers with the similar products they have purchased before. This technology mainly looks for the association of features between the user profile and item attributes. First, the features of item attributes must be analyzed to determine and to compare the data on the user preference profile. Second, the process is to find out the commodities that the users are likely to be interested. Finally, provide services by recommending commodities to users [175]. CB recommendation is mainly extended from information retrieval, known as Feature-based recommendation. This is because this model emphasizes the analysis of item attributes.

CB recommendation is susceptible to retrieving content attributes, so it is more likely to be applied in the recommendation fields related to commerce, information, and education.

With regards to E-commerce, the application fields may include personalized business services [154] and mobile commerce.

An example of application in E-commerce is as shown in Figure 5. The architecture of recommender system in figure 5 basically covers several parts.

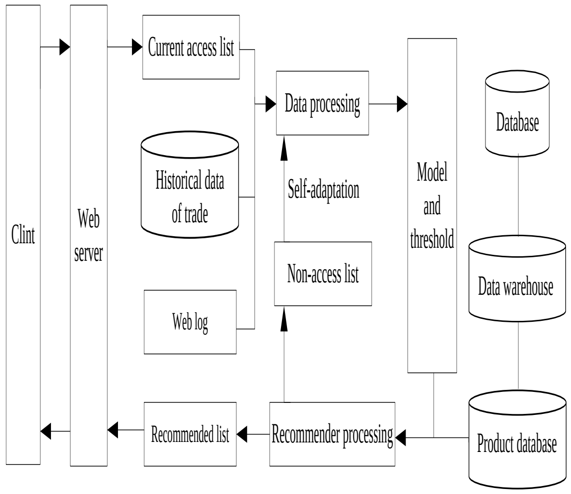


Fig. 5 Application in E-commerce Architecture of a Recommendation System [60]

(1) Data acquisition: Acquires user preference feature data by the received information, historical transaction records, and website records.
(2) Data Processing: Data are acquired by filtering or screening.
(3) Recommendation Processing: Recommender model and initial threshold are generated from data comparison. The system may automatically adjust a recommender model and initial threshold through the recommender procedures.
(4) Recommendation Results: The results of system processing will be listed out and recommended to users.

Conventionally, CB recommendation technology is often applied to the information-related fields including the analyzable content or description. It is easy to analyze because its content or correlation attribute is extractable. Such method builds the vector based on items' content or attribute. It usually applies the cosine of vectors to determine if there is any correlation between two objects. The smaller the angle between the vectors of two objects will be, the larger the similarity, and vice versa.

Some famous systems application of CB recommender systems are described in the following.

(1) NewsWeeder [118]: NewsWeeder is a filtering system for Netnews that provides the interface of evaluating articles for user through Mosaic browser. The system compiles and analyzes user evaluation data to build a user profile and thereby recommend the unread articles to user by user be profiles.
(2) InfoFinder [89,90]: Acquire categories of user preference through sets of messages or other on-line documents. InfoFinder differs from other content retrieval system. Its characteristics lie on using heuristic search techniques to acquire meaningful phrases. The advantage of such system is the correct understanding of user interests in the absence of document samples.

CB Recommendation aims for commodities and therefore appropriate recommenders are beyond consideration. The following advantages provide more extensive applicability to the study of personalized recommendation:

(1) Recommend users without the reliance on other user information.
(2) Provide recommendation based on the unique preference of users.
(3) Recommend new commodities to users.
(4) Give the reasonable explanation of recommending this commodity.

CB Recommendation may generate recommendations based on personal preference, and it does not need to rely on other similar users for the generation of recommendation. CB is highly used for personalized services. However, the process of CB recommendation may encounter some issues [157]:

(1) Difficulty of analyzing multimedia projects [86,157]: Most websites today offer the multimedia information, including sounds, photographs, and videos. The features of such multimedia could not be easily retrieved and difficultly compared for similarity. Therefore, some fields (such as movies and music) could not obtain the effective recommendation.
(2) Requirement for user feedback: The feedback information increases user burden, so most users are reluctant to make the informational feedback. Therefore, it will lead to an insufficient rating. As a result, insufficiency will result in the lowering system efficacy. Some researchers [11] believe this issue could be solved by adopting implicit feedback in order to resolve user reluctance

in spending time and efforts on the informational feedback.

(3) Synonym and polysemy: Terms describing items usually containing a synonym and polysemy. A recommendation adopting item filtering will be inaccurate without the establishment of sound word relationship [11].

(4) The influence of user interests: The prediction accuracy of user interests will affect the recommendation results. If the recommendation system misinterprets user interests, it will recommend the items that users are not interested at all [128].

(5) New User Problem [22]: A new user did not leave any usage records on the system before, and therefore no accurate and real-time analysis could be provided. Hence, the final recommendation results will be affected. It is unquestionable that many researchers have proposed good solutions such as: Ask some questions which might facilitate the discovery of user preference upon a user's first-time login to the system, or use other recommendation technology to prevent users from not trusting the system and lowering their willingness to use.

(6) Item Limitation [22]: Users could only receive the similar recommended items similar from the past and could not find the correlation between the historical preference records of users and the object items to be recommended. There is no flexibility to search for the potential preference.

(7) Filtering Limitation：Quality, style, or point of view of the same items could not be filtered. In the example of articles, such method could not effectively differentiate between the two articles that have the same title but the different content and quality.

To solve the aforementioned limitation of CB recommendation, a second system, CF is used for the improvement. CF recommendation could analyze the attribute features of items and cluster similar interests, preferences, and behaviors of similar users. The system could predict user preference and enhance recommendation quality. The recommendation result of CF is far better than CB recommendation.

3.2. Collaborative Filtering (CF) recommendation

When customers hesitate to make decisions in daily life, they often rely on other people's word-of-mouth or introduction to help them make a decision on travel, movies, books, or food [133]. For example, Tom and Joe both have the same preference on movies. If Tom wants to see a movie but has not decided which one, he can make the final decision through the help of Joe's recommendation. The fundamental concept of CF helps customers to obtain the appropriate recommendation through individuals or groups who have similar interests or characteristics. Use CF system to recommend products to users in accordance with the following three steps [82]:

(1) Generate user profile: Construct a user profile from the user's historical transactions or item rating data.

(2) Neighbors Data: The system can search for the groups that are similar with target user by using statistics or mechanical learning. These groups are known as nearest neighbors. The system will calculate the preference similarity with other users based on the user profiles. In other words, users within the nearest neighbors will have the similar item preference or rating.

(3)Generate recommendation: Introduce products purchased by other members within the same group to users. If the recommendation is combined with a weighted concept, the system will generate the sequential recommendation of products.

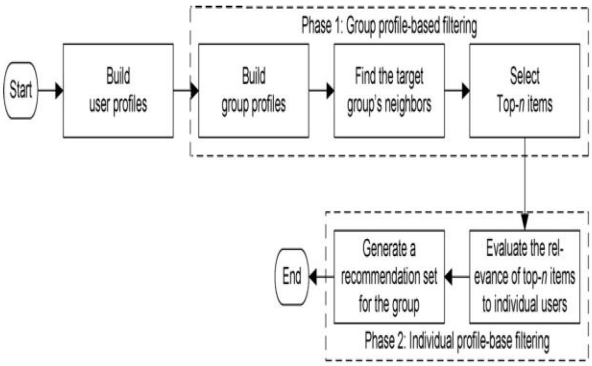


Fig. 6 Application of Recommendation to Online Community [82]

CF is currently the most popular type technology of recommendation system [6,116,139,176] because it does not require the analysis of product content. Therefore, CF can solve the problem of CB when products or document content are difficult to analyze. CF will make the recommendation to target users according to the clusters' interests, experiences and preferences that are the same as the target users. Although the recommended products or information differs from the user's previous preferences, the user's potential requirement could be developed, i.e., turning the browser turns into a buyer. Through the item rating of users or the information of product purchase, the CF recommendation system will discover groups who have similar preferences with users. Once such a group is discovered, users will be provided with recommendations using various algorithms [3,61,133]. For this reason, collaborative filtering is also known as social filtering.

Figure 6 shows a type of application of recommendation to online community. The system process is divided into two parts: Group profile-based filtering and individual profile-based filtering. In the first part, a group profile is established to find out the target neighbors that have similarity with users by similarity calculation. The most appropriate product items will be recommended. In the second part, we calculate the correlation between the items that a similar group and users like the most.

Goldberg et al. [49] suggested in his 1992 research that the CF recommendation system is mainly applied in the Tapesry system, which is a mail system developed by Xerox Palo Alto. The main objective of this system was to filter e-mail and was subsequently applied to all electronic documents. Users build query using the query grammar of TQL (Tapestry Query Language) and filter out the email through different query. Nonetheless, such system still passively requires users to build a query in order to filter out the mail that the users like instead of actively making recommendation to users. The operations of such technology are, firstly, finding out a group of users with the same preference. Secondly, analyzing the same interests or preference of social members through the past historical records. Thirdly, calculating the similarity of preference behavior among users in order to find out the nearest users who have similar preferences. Finally, it recommends potentially interested information users have not touched through the comments or recommendation of nearest users. Consequently, the system will take the preference of social members who have the same interests as users into consideration. In other words, the system will use other user comments as recommendation of products to target users. Hence, it is possible that the recommended products could differ from the previous preference of users.

Quite a few researchers had proposed relevant theories on CF recommendation. Resnick et al. [143] proposed that CF uses a group view to recommend items to users. It collects user historical transaction data of the product or service preference and divides users into different groups using correlation analysis. Each group consists of users with high relevance. CF can find out the groups who have similar preferences with users and recommend the product or service to the users within the same group. Schafer et al. [153] suggested that the recommendation technology of People-to-People Correlation is collaborative filtering and the recommendation technology based on the correlation among users. Carenini et al. [24], Bobadilla et al. [18], Jeong et al. [71,72], and Breese et al. [20] followed the algorithm adopted by collaborative filtering to roughly divide the system into two categories, i.e., Memory-based [19,72,141,164] and Model-based [19,141,164]. The descriptions of these two concepts are as follows.

(1) Memory-based CF: Use records in database for analysis. For example, after calculating the similarity and correlation, recommend the items that have the highest correlation with user preference [20]. Calculate and analyze user historical records during recommendation to find out the adjacent groups who have similar preferences with users. The most common method is the Nearest Neighbors [4,17,50,151,176].

(2) Model-based CF: Use mathematical model or mechanical learning model to calculate and predict which items the users currently prefer or need. The purpose is to use user historical records and construct a user preference model through mathematical statistics or mechanical learning. Use this preference model to generate recommendation [20]. For example, Latent Semantic Indexing (LSI) utilizes Singular Value Decomposition (SVD) to acquire the adjacent group of specific user [4,51]. Currently, some common methods include: Latent Semantic Indexing (LSI), Association Rules, Bayesian Network, or Regression Analysis.

Yang et al. [178] divided CF into two categories in accordance with the incident correlation used in collaborative filtering:

(1) Analyzing and prediction based on User-based [164] correlation: The core concept is the assumption of a specific degree of similarity in people-to-people behaviors. In

other words, customers with similar purchasing behavior will purchase similar products. GroupLens refers to such type of system [4,98,99,116,126,139,156].

(2) Analyzing and prediction based on Item-based [164] correlation: It is the assumption of a specific degree of correlation between items. In other words, the purchased products of customers usually contain correlation [4,20,98,99,116,139,151]. For example, customers usually purchase memory cards and batteries when purchasing the digital cameras.

Sarwar et al. [150] argued that the recommendation process of collaborative filtering should contain three major tasks, i.e., representation of input data, neighborhood formation, and recommendation generation as shown in Figure 7.

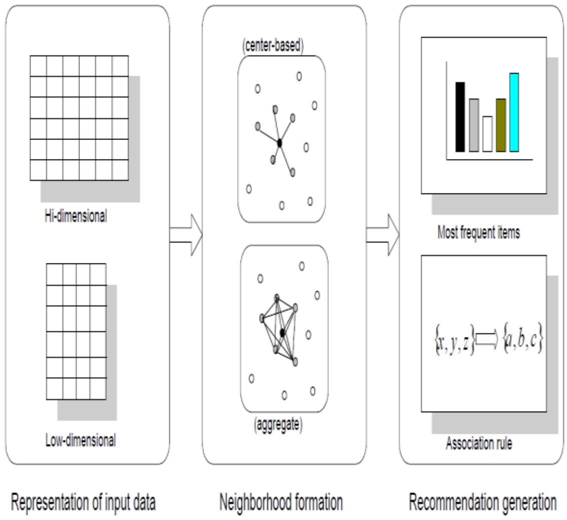


Fig. 7 Collaborative Filtering System Process [150]

(1) Representation of input data: Customers' past purchasing behavior is stored in a matrix. As shown in Figure 8, u denotes customers, i denote the index of customers with a maximum number of n; p refers to items, j denotes the index of product item with a maximum number of m. The rij in the matrix refers to the rating feedback information on product item j given by the customer i.

(2) Neighborhood formation: The most important step in collaborative filtering recommendation system is to calculate the degree of preference similarity between customers as the reference for future recommendation.

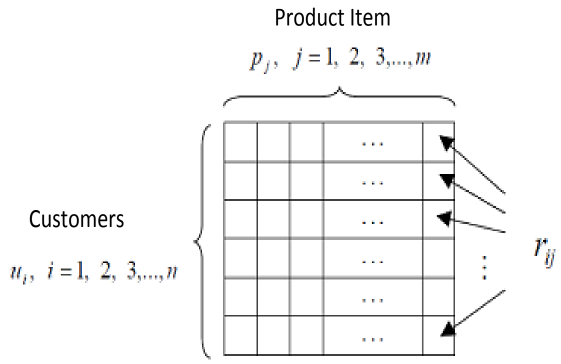


Fig. 8 Input Data Representation

(3) Recommendation generation: After acquiring customer preference similarity, the customer group with higher similarity becomes the reference objects of recommendation. The most popular items of recommendation are found from the customer group with similar preference.

Ringo [137,156] and Bellcore Video [62] Recommender system provides users with a ranked list of products. Such approach is the one of the major functions for the development of recommendation system today. This approach also drives the development of recommendation system into a more mature stage. It is widely applied in various commercial systems, including Amazon, eBay and CDNOW. They are all examples of successful E-commerce recommendation system in websites. The researchers' application fields in the study of CF recommendation including: Commerce, information, industry, web-service, and education. In the past, many application of collaborative recommendation were developed (as shown in Table 4-2) and they are briefly introduced as follows:

(1)Tapestry [10,26,28,42,49,128,141,144,151,156,164,177,188]: It is the first recommendation system that adopts CF (1992). The initial purpose was to filter out email and then was expanded to all electronic documents [17]. In order to build a user profile manually, such system allows users to consult the documents and the remark notes of others [26]. The remark shows if the reader "likes" or "does not like" that document, the system will notify users when it discovers the documents meeting query criteria through the filtering process of comparing documents and note files.

(2)GroupLens [10,26,28,87,121,126,128,143,144,149,151,1

56]: A news-based collaborative filtering system that helps users find the articles they like from the massive news database. GroupLens adopts an open architecture, consisting of news clients and rating servers. News clients allow users to make ratings by 1-5 after reading the articles [26,51]. Rating servers are the collection and sending of rating. According to the past article ratings of users, rating servers can predict the rating of articles that are not read by users to help them decide whether they want to read that news.

(3) MovieLens [52]: A movie recommendation website that uses the conventional collaborative information filtering technology provides the recommendation of movies, DVDs, and VHS tapes [121]. The website provides a user-friendly interface, where a user may build the rating of movies that user has seen to build the user interest profile. Nonetheless, the system will require new members to give 20 movie ratings at least before making the appropriate recommendation.

(4) Ringo [28,137,149,151,156,157]: A music recommendation system is developed by the Massachusetts Institute of Technology. Such system arranges and analyzes user ratings on the music and calculates the similarity between users. The system then groups the users of higher similarity together and recommends the music preferred by other users within the same group to the user [121]. It is a social information filtering system that uses conventional collaborative filtering technology to build profile based on user ratings on the music album. The system provides the personalized music recommendation service to users via email and WWW. In the calculation of user similarity, the system uses the techniques of Pearson Correlation, Constrained Pearson Correlation, Vector Cosine, and so on. Four different recommendation system algorithms are suggested in this system [51].

(5) Amazon.com [7]: This website contains more than 1.2 billion customers and several million products. To overcome scalability issue, the system uses the collaborative filtering technique of item-to-item to generate the table of similar-items offline. Then, the system recommends other similar products online according to customer purchased and rated products.

(6) PolyLens [133]: It is a recommendation system that recommends movies to group members [82]. Its main object of recommendation is groups.

The difference of the recommendation between CB and CF Recommendation systems lies on people instead of content analysis. Therefore, CF can supplement shortcomings in CB and recommend various styles of content. Herlocker et al. [61] argued that there are many advantages in collaborative filtering technology. They are as follows:

(1)CF technology can support the recommendation whose content is not actively processed.

(2) CF technology is able to recommend items based on quality or experience.

(3) CF technology is able to recommend items outside of predicted scope.

Collaborative filtering technology is now deemed as a very important technology for recommendation system, and it can generate the recommendation according to the quality, style, or attributes of items. It can also cooperate with users who have similar preferences to recommend the items outside of predicted scope. However, there are some inevitable limitations:

(1)Sparsity [2,10.6,28,32,35,37,38,71,72,103, 125,128,146,151,152,164,181]:CF recommendation often deals with a large number of products or items as the objectives of evaluation and recommendation. Therefore, the rating matrix or user rating profile may be very sparse. This will lead to inaccuracy when calculating the similarity. For example, if an E-commerce website has 10,000 members and runs 1,000 products, then the rating matrix will have size of 10,000 x 1,000. However, a customer may give a rating of a few products, and it is obvious that most of the products are treated as unrated items. Therefore, this matrix will be very sparse. Hence, this problem is the most common issue in CF recommendation system now and also the most difficult problem to solve for CF. Many researchers [2,28,35,38,71, 72,103, 125,146,147,151,152,181] who have proposed various solutions to deal with it. The scholars [72] utilized semi-explicit rating (SER) to overcome the data sparsity problem in the user-item matrix.

(2) Scalability [2,21,28,37,72,125,151,182]: Excessive data in database will lead to the system overload. For example, using the nearest neighbors to calculate the similarity

among users, the complexity of the algorithm grows in geometric square with the user's historical transaction data or product quantity. Scalability is usually a common problem when dealing with large database. Many researchers [2,28,38,72,108,125,151] also have proposed solutions to deal with it.

(3) Synonymy [150]: The problem of synonymy refers to the same terms with different names. Because the CF recommendation system may fails to distinguish the implicit significance of rating items (products, information), the system could not find the implicit correlation among products and determines that the products or the information are dissimilar. Consequently, the products of recommendation will substantially decrease.

(4) Cold Start[5,14,22,25,28,32,35,50,71, 79,95, 102,103,116,149,173]: When CF recommendation system recommends for users, it will search for the suitable neighbor group through the rating information of the user. However, this is one difficult issue for new users because the system does not have any data related to this user. Therefore, the system could not make the recommendation for new user. Simply put, there are no sufficient users and product information, so it is difficult for recommendation system to calculate user similarity. The cold start problems are divided into two categories:

(a) New-System Cold-Start: When the system is initiated, it cannot make the recommendation, i.e., a system bootstrapping problem. It is because there are insufficient user ratings and records, or individual profile data. The system performance is not ideal at the very beginning because the group similarity cannot be obtained accurately.

(b) New-User Cold-Start [10,22,79,128]: For new user, when the system fails to search the useful information for recommendation, its performance will not be able to meet new user requirement.

(c) New-item Cold-Start [22,32,128]: Because item recommendation through CF must be rated or purchased by the users. A new item has to wait a period of time after the item is purchased.

Many researchers [5,22,25,28,35,50,71, 79, 95,101,102,103,149,173] have proposed measures in response to this issue. For example, recommendations could be made through popular and general interests, and the system can also actively provide some samples for users to choose after logging into the system. Therefore, the system could rapidly obtain user information and finally give the appropriate recommendation. Many studies proposed Hybrid-based recommendation system to solve this problem and to improve the efficacy.

3.3 Hybrid Recommendations

Hybrid recommendation refers to the system that combines Content-based (CB) and Collaborative Filtering (CF) or other type of recommendation systems [22]. According to the characteristics of problems, hybrid recommendation combines the advantages of different techniques to compensate inadequacies of various types of recommendation techniques [131]. Because the CB recommendation and CF recommendation has its own advantages and limitations, hence, Balabanovic and Shoham [11] proposed a hybrid recommendation system that integrates CB recommendation and CF recommendation to achieve the effective recommendation. Hybrid recommendation is divided into the following four methods [22]:

(1) Implementation CB and CF separately, and then combine the predictions of both methods to make the recommendation.
(2) Integrate some CB characteristics with CF recommendation.
(3) Integrate some CF characteristics with CB recommendation.
(4) Integrate the characteristics of CB and CF to build an overall unified model.

Adomavicius et al. [3] suggested that collaborative based and content filtering recommendations can be integrated into Hybrid recommendation. As a result, the system may use different modules to generate better recommendation results and enhance the effectiveness and accuracy of recommendations according to the recommendation environments. Li et al. [102] divided the modules of hybrid recommendation into two types, including [102]:

(1) Linear Combination Model (see Figure 9): The main concept of this model is to multiple the forecast values of content-oriented and collaborative filtering calculation by a weighted value and to add them up.
(2) Sequential Combination Model (see Figure 10): This model is implemented in two steps:
Step 1. CB will be used to search for users who have similar preferences.
Step 2. CF can be used for the prediction.

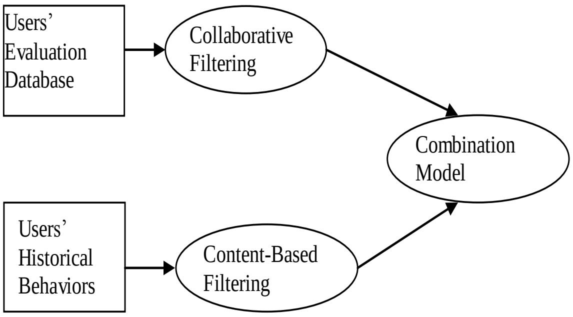


Fig. 9 Linear Combination Model Architecture [102]

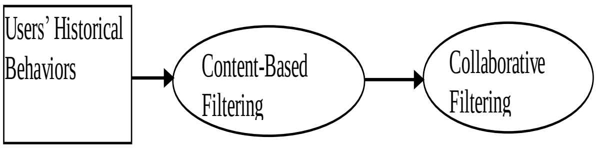


Fig. 10 Sequential Combination Model Architecture [102]

There is a great variety of applications using hybrid recommendation. We introduce the three most common applications below.

(1) Fab [11,13,26,102,103,128,144,154] is a recommendation system using hybrid filtering. The recommendation contents consist of websites, news, or online articles [121,182]. The system is divided into two parts in terms of the applications of recommendation websites:

(a) Collection Agent: It is responsible for collecting the websites of specific themes and the users' evaluating data of these websites.

(b) Selection Agent: It records the preference data of each user.

The operational methods of Fab are as follows: After collection agents find these websites, they deliver these websites to similar users from the themes that the preference and collection agents are responsible for. For example, the agents responsible for stock investment websites will deliver the relevant websites to users who prefer this category. After the users receive the websites and evaluate, they deliver the websites to selection agents to update the data, and then send the data to the previous collection agent for updating. Finally, these websites will be sent to users with similar preferences. Therefore, CF recommendation is referred to as "websites with high rating will be sent to users with identical preferences" in this system, and CB recommendation is treated as "user profile data built by agents."

(2) Intelligent News Filtering Organizational System (INFOS) [127]: INFOS builds the interests and preferences based on users' active feedback. It also uses this data to predict whether the new articles meet user interests. The INFOS's procedures are as follows: Users first read an article, and INFOS will request users to evaluate the article. If users like the article, they reply "accept". If they do not like the article, they reply "reject." If users are unsure, they reply "unsure." When users continue to read the next article, new articles will be rearranged according to these interests and preferences. INFOS will learn from user feedback and behavior. Such filtering method is a hybrid technology. It employs Hill Climbing method based on the keyword and WordNet of knowledge-based concept.

(3) RAAP [44,102,103]: RAAP recommends similar websites to users based on the user's browsing history. To help users with the classification of browsed websites, Pearson Correlation Coefficient (PCC) is applied to calculate the similarity of each website based on the classification.

4. SUMMARY

4.1 Summary of Recommender System Application

Most applications of a recommendation system are related with E-commerce and information filtering, and provide the customer with better services. From the 189 literatures, this research reviewed various types of recommendation systems and application domains were introduced. There are many famous E-commerce websites including Amazon, Yahoo, Moviefinder, MovieLens, CDNOW, Drugstore, and Launch that incorporate a recommendation system in the service, and many researchers apply recommendation systems in the service of documentation, music, movie, news, and so on. Through the progress of information system, breakthrough of website technique, and the rise of the cloud concept, mobile recommendation are becoming increasingly popular. These include message recommendation, music recommendation, product recommendation, and news recommendation.

This research integrated 189 papers concerning recommender system's research, and reorganization recommendation system common classification, i.e., Non-Personalized Recommendations, Attribute-Based Recommendations, Item-to-Item Correlation Recommendations, People-to-People Correlation Recommendations, CB, CF, and Hybrid-base. Most researchers divide the recommendation techniques into three categories: CB recommendation, CF recommendation, and Hybrid-based recommendation. Each one has its own characteristics, usage, and representative system. Of course, there is no doubt that CB and CF has their own shortcomings. For example, CF can solve the problems of multimedia items, synonyms, and polysemy which cannot be handled through the CB technique. The problems of sparsity, scalability, and cold start may be encountered when applying recommendation technique of CF, which is why researchers hope to improve these defects. Hybrid-based integration CB and CF technical advantage are suitable applications in the recommender system's domain.

4.2 Conclusion

This study details the evolution and origin of the recommendation system to enable researchers to gain relevant insights, which are considered important especially for scholars engaged in preliminary study of the recommendation system. Secondly, the 189 targeted articles of the recommendation system related researches were organized, classified, and summarized. The applications of the recommended system were then sorted out, allowing researchers to understand in which fields the applications were the most applicable and the areas to dwell on in the future. Based on the evidence in Table 1, it can be seen that the Internet and Web related researches still remain the major direction for studying the recommendation system. However, owing to the prevalence of cloud computing and mobile services, the recommendation system must take a new direction. Hence, scholars may move toward this development. Moreover, based on the data in the SDOL database, it was found that the recommendation system researches have rapidly increased in number over the years (as shown in Fig. 3), thus indirectly explaining their impact on businesses and individuals and their being considered a good inspiration for researchers. However, in terms of recommendation classification techniques, three types of classifications, namely, content, collaborative filtering, and mixed, have been most frequently covered by scholars. Regarding the early researches on the recommendation system, most have been content technology-based, but recently hybrid technology has generally been adopted as the basis. This is considered a good reference for scholars in their research. Furthermore, the well-known systems in the recommendation system were described to enable scholars to better understand the recommendation system and to serve as a sound reference for their future research. Finally, the advantages and disadvantages of the three classification techniques, as well as the improvement methods were summarized, which will contribute positively to help researchers achieve technical breakthroughs.

4.3 Future Research and Recommendations

Concerning future research, “researches on ways to automate the recommendation system analysis and literature analysis related techniques” will be added. Of course, the common recommendation system related techniques will be analyzed and discussed. With our effort, the recommendation system review will become more complete.

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