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Classification and Comparison of the Hybrid Collaborative Filtering Systems

F. S. Gohari *, M. J. Tarokh

Department of Industrial Engineering, K.N. Toosi University of Technology, Tehran, Iran

ABSTRACT

Recommender systems have become fundamental applications in overloaded information domains like e-commerce. These systems aim to provide users with suggestions about items that are likely to be of their interest. Collaborative Filtering (CF) is one of the most successful approaches in recommender systems. Regardless of its success in many application domains, CF has main limitations such as sparsity, cold start, gray sheep and scalability problems. In order to overcome these limitations, hybrid CF systems have been used which combine CF with other recommendation approaches. This paper provides a comprehensive survey of hybrid CF systems; it also provides a classification for these systems, explains their strengths or weaknesses and compares their performance in dealing with the main limitations of CF.

Keywords: *Recommender systems, collaborative filtering, hybrid collaborative, filtering systems.*

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1. Introduction

Recommender systems began to appear in the market in 1996 [1] in order to deal with the problem of information and product overload. Recommender systems produce individualized recommendations as output or guide the user in a personalized way to interesting items or products in a large space of possible options. Such systems are widely used in an environment where the amount of on-line information outstrips any individual's capability to survey it [2]. Nowadays, recommender systems are used by many of the largest e-commerce Web sites to help their customers [3].

Two basic entities in all recommender systems are: the user and the item. A user, who utilizes the recommender system is called *active user*. An active user provides his opinion about past items, which is usually expressed in the form of ratings. The recommender system applies a filtering algorithm on the input ratings and generates suggestions about new items for the active user [4].

*Corresponding author

E-mail address: fgohari@mail.kntu.ac.ir

One of the most familiar and commonly used filtering algorithms is collaborative filtering (CF). CF recommends items based on rating information of like-minded users (known as neighbors) on the items [5]. CF technology brings together the opinions of large interconnected communities on the web, supporting filtering of substantial quantities of data [6]. CF has been used fairly successfully in various domains. However, it has main limitations such as sparsity, cold start, gray sheep and scalability problems [2], [7].

Sparsity [8] arises when the number of ratings obtained from users is usually very small compared to the number of ratings that must be predicted. This has a negative effect on the final predictions because it affects the selection of the neighbors [9].

Cold-start [10] problem occurs when it is not possible to make reliable recommendations due to an initial lack of ratings [11]. Two types of cold start problems are: (1) new user problem [12], and (2) new item problem [13].

Gray sheep [14] problems refers to the users whose opinions do not consistently agree or disagree with any group of people and thus do not benefit from CF [15].

Scalability [16] problem arises because CF searches the whole ratings database and thus it suffers from poor scalability when more and more users and items are added into the database [17].

In order to overcome these limitations, some hybrid CF systems [15] have been used which combine CF with other recommendation approaches (e.g., demographic, content-based, knowledge-based, etc.). Each hybrid system addresses one or more limitations of CF and it has its own strengths and weaknesses.

In this paper, we provide a comprehensive survey about hybrid CF systems and their strengths or weaknesses. For this purpose, we classify hybrid CF systems into different categories and review the previous works related to each category. Then, we investigate the strengths and weaknesses of each category in dealing with the main limitations of CF.

The rest of this paper is organized as follows. The following section reviews the related works and the original contributions of this work. In Section 3, we explain the methodology of this survey. Section 4 focuses on the existing recommendation approaches and Section 5 briefly presents different hybridization methods for combining two or more approaches. In Section 6, we demonstrate hybrid CF systems, classify them and review the previous works related to each class. Comparison of the hybrid CF systems is explained in Section 7 and finally, conclusions are discussed in Section 8.

2. Literature Review

Due to the growing complexity of recommendation algorithms, different survey papers have been published in this area. Burke [2] surveys the different recommendation techniques being researched and examines the range of hybridization techniques that have been proposed. Herlocker [18] reviews the key decisions in evaluating collaborative filtering recommender systems. In addition, the author introduces empirical results on accuracy metrics that provide some initial insight into how results from different evaluation metrics might vary.

Perugini et al. [19] take a connection-oriented perspective and survey recommender systems from such a perspective. They posit that recommendation has an inherently social element and is ultimately intended to connect people either directly or indirectly. Adomavicius and Tuzhilin [20] present an overview of the field of recommender systems and describe various ways to extend capabilities of recommender systems. Schafer et al. [6] introduce the core concepts of CF, its primary uses for users of the adaptive web, the theory and practice, design decisions, evaluation and privacy issues. Candillier et al. [21] review the main methods of CF, compare their performance and highlight the advantages and drawbacks of each approach. Su and Khoshgoftaar [15] introduce CF tasks and their main challenges. They also expose an overview table of CF techniques. Park et al. [22] review 210 articles on recommender systems, and then classified those by the year of publication, the journals in which they appeared, their application fields, and their data mining techniques. Lü et al. [23] review recent developments in recommender systems and discuss the major challenges. They also compare and evaluate available algorithms and examine their roles in the future developments. Bobadilla et al. [11] provide an overview of recommender systems; explain their evolution, provide an original classification for these systems and identifies areas of future implementation.

The aim of this paper is to analyze the hybrid CF systems that have not been dealt carefully in the previous papers. The contributions of this paper are summarized as follows:

- Studies main types of recommendation techniques as well as semantic-based and context-aware approaches.
- Provides a comprehensive survey on hybrid CF systems, presenting a novel classification for these systems.
- Presents a novel overview table informing the summary of previous works related the different categories of hybrid CF systems. It includes type of CF algorithm, hybridization method and domain of experiment.
- Compares the performance of each identified category in dealing with the main limitations of CF, such as sparsity, cold-start, gray sheep and scalability problems.
- Presents a novel overview table outlining strengths and weaknesses of the different hybrid CF systems.

3. Methodology

The main goal of this paper is to provide a survey about hybrid CF systems as well as to outline their strengths and weaknesses. An initial study was performed to determine the most relevant papers on hybrid CF systems published between 1994 and 2014. For this purpose, we searched the following electronic journal databases:

- ACM Portal
- IEEE/IEE Library

- Science Direct
- Springer Link
- Emerald Insight
- ProQuest
- Wiley online Library
- JSTOR

First, 163 papers were selected from journals, with a higher priority for current and for often-cited articles. Next, we extracted from these 153 papers the most significant papers based on the following criteria: (1) the transcendence of the subject according to the keywords, title and abstract; (2) its contribution; (3) the number of times the article is cited; (4) articles published in journals with an impact factor were preferred over conferences and workshops; and (e) recent articles were preferred over articles published many years ago. Figure 1 shows a temporal distribution for the referenced papers in this survey.

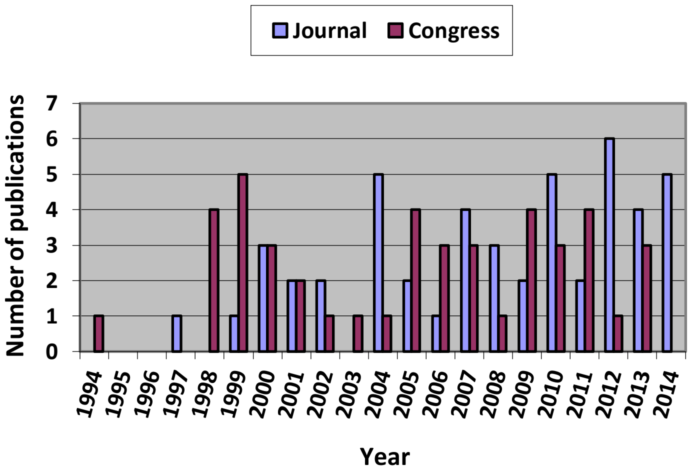

Fig 1. Temporal distribution of the referenced papers

4. Recommendation Approaches

In this section we review different approaches for generating recommendations in a recommender system.

Based on the classification proposed by Burke [2], we can distinguish four main types of recommendation techniques: collaborative filtering, content-based, demographic and knowledge-based. In addition to the above techniques, we also consider two other recommendation approaches which have emerged recently: semantic-based and context-aware approaches.

4.1. Collaborative Filtering (CF)

CF is the most popular recommendation technique in current recommender systems. It suggests to each user items that were appealing to other users with similar tastes. This approach can be either memory-based, using the entire rating matrix to make recommendations, or model-based, in which a model is derived from the historical rating data and then used to finally make predictions [2].

Memory-based methods are simpler and seem to work reasonably well in practice and new data can be added easily and incrementally [24]. Memory-based algorithms usually fall into two classes: User-Based (UB) and Item-Based (IB) approaches [25], [26].

In UB methods [27], [28], a subset of users is chosen based on their similarity to the active user (commonly called the *neighborhood*), and a weighted combination of their ratings is used to predict the ratings for the active user. IB methods [29], [30] share the same idea with user-based method. The only difference is IB approaches try to find the similar items for each item [31]. The most extensively used similarity measures in memory-based methods are Pearson Correlation Coefficient (PCC) [27] and Vector Space Similarity [28]. With millions of users and items, user-based recommender systems suffer serious scalability problems. In contrast, item-based recommender can quickly recommend a set of items because item-item similarity matrix is generated offline. However, there are experiments showing that UB provides more accurate recommendations than IB [32].

In model-based methods, predictions can be computed quickly once the model is derived. However, they have the overhead to build and update the model, and they cannot cover as diverse user ranges as the memory-based methods do. Model-based methods improve system scalability at the expense of accuracy [33]. Model-based recommenders have used a variety of probabilistic models including Bayesian network models [28], latent class models [34], regression models [35], clustering models [36], [37], [38], etc.

Common limitations of CF systems are sparsity, new user/item (cold-start) and gray sheep problems [7], [39]. CF suffers from sparsity problem, because most users do not rate most items. With a sparse ratings matrix, a recommender system becomes unable to find similar neighbors and generates poor recommendations. Model-based CF handles the sparsity better than memory based ones. For example, model-based approaches that employ a dimensionality reduction technique, such as singular value decomposition, reduce the sparsity problem [2].

One typical problem caused by the data sparsity is the cold start problem. This means that CF fails to generate proper recommendations for a new user, having very few ratings. Actually, to be able to make accurate predictions, the system must first learn the user's preferences from the ratings that the user makes. Therefore, CF becomes unable to make accurate recommendations for a new user. Similarly, CF would be unlikely to recommend new items that have none or few ratings [7].

Another problem of CF is the gray sheep problem. Actually, CF works best for a user who fits into a niche with many neighbors of similar taste. It does not work well for users who fall on a border between existing cliques of users [2]. Also, in the case of item-based CF, an item that has low correlation coefficients with other items cannot be recommended, though it is possible that some users may like it.

4.2. Content-based (CB)

CB recommender learns a profile of the user's interests based on the features present in items the user has rated. The type of user profile derived by a CB recommender depends on the learning method employed [2]. CB recommender provides recommendations by comparing representations of content describing an item to representations of content that interests the user [40]. Due to the syntactic nature of this approach, it only detects similarity between items that share the same features [41]. Actually, in this approach, the user is limited to being recommended items similar to those already rated (over-specialization problem). Also, CB techniques are limited by the features that are explicitly associated with the objects that these systems recommend. Other main limitation of this approach is new user problem [20].

4.3. Demographic (DM)

Demographic recommender categorizes users based on their demographic attributes and makes recommendations based on these categories [2]. Demographic data refers to information such as the age, the gender and the occupation of the user. DM recommender can generate proper recommendations to new users before they have provided many ratings [42], [43]. So, this approach does not have the new user problem; instead it has the problem of gathering the requisite demographic data and gray sheep problem [2]. Also, a new item that has none or few ratings cannot be easily recommended.

4.4. Knowledge-based (KB)

KB recommender suggests objects based on inferences about the relationship between a user's needs and preferences. The user profile can be any knowledge structure that supports this inference. Despite the previous techniques, the quality of this approach does not rely on large historical data set. Also, KB approach can respond quickly to the changes of user's preference, but it has the problem of requiring knowledge engineering [2].

4.5. Semantic-based (SB)

The rapid increase in the amount of information available on the internet has made it difficult to search and find objects that may be of interest for users. The reason is that the most of today's Web content has been designed to be readable only by humans, and so the meaning of Web content is not machine-accessible. The Semantic Web technologies have emerged to overcome this problem [44]. These technologies represent Web content in a form that is more easily machine-processable [45].

Recommendation systems can take advantage of semantic reasoning to improve the recommendations' quality [46]. So, as a new direction, semantic-based recommender systems has emerged that focused on the semantic information underlying the users or items [47]. SB recommenders use Semantic Web technologies and generate recommendation based on a knowledge base which is defined through conceptual maps or ontologies [48]. Such systems improve the quality of recommendations by allowing the recommender to make inferences based on an additional source of knowledge [47].

SB systems are a special kind of knowledge-based systems. Actually, Semantic Web technology is one of many technologies which can be used for modeling a knowledge base. Semantic Web technologies provide machine-readable knowledge and it improves knowledge representation. Ontologies, as one of the key Semantic web technologies, formally represent knowledge as a set of concepts within a domain and the relationships between them. The formal semantics underlying ontology allows the automated reasoners to infer new knowledge [44], [45].

Semantic recommender systems can be used to limit the sparsity and new item problems of CF [49] and over-specialization of CB systems [41]. In recent years many recommender systems have appeared that use Semantic Web technologies for recommending foods [50], tourism services [51], personalized TV contents [52], experts [53], scientific articles [54] and job opportunities [55].

4.6. Context-Aware (CA)

CA recommender is useful in dynamic recommendation's environment in which the users' decisions depend on many things in their surrounding context. Context is any information (such as location or time) that can be used to determine the situation of an entity [56]. Context-aware systems [57], [58], [59], [60] can adapt their recommendations to different places or times.

5. Hybrid Recommendation Methods

Hybrid systems combine two or more recommendation approaches to leverage the strengths of each individual approach. Seven basic hybridization methods are as follows [2]: (1) Weighted, combining the scores of each approaches using a weighted method for producing a single recommendation**;** (2) Switching, switching between different recommenders depending on the current situation; (3) Mixed, presenting the results from different approaches at the same time; (4) Feature combination, combining features from different approaches together into a single recommender; (5) Cascade, refining the results of one recommender by another in a cascaded way; (6) Feature augmentation, augmenting the input of one approach by the outputs from another; and (7) Meta-level in which the entire model produced by one recommendation approach is utilized by another.

6. Hybrid Collaborative Filtering Systems

Hybrid CF systems combine CF with other recommendation approaches to make recommendations [15]. Hoping to avoid limitations of CF and improve its performance, memory-based or model-based CF can be combined with each of the previously mentioned approaches based on different hybridization methods. So we can classify hybrid CF systems into:

6.1. Combining CF with CB

Most of the previous researches have used the combination of CF and CB in order to cope with new item, sparsity and gray sheep problems of CF. This combination can also make collaborative recommendations between users who have rated items with similar content any of the same items (as long as they have rated) [61]. Some researches in this area are as follows:

User-based CF: Claypool et al. [39] proposed a weighted hybrid recommender system for an online newspaper, in which the weights of the user-based CF and CB can change over time to reflect the change in user tastes. The PTV system [62] is a TV program recommender that mixes recommendations from CB with those based on user-based CF. "Content-boosted CF" [63] is a feature augmentation hybrid approach which uses a naive Bayesian text classifier to convert a sparse ratings matrix into a full ratings matrix; and then uses user-based CF to provide recommendations. “Sequential mixture CF” [64] is another feature augmentation hybrid approach that employs *TAN-ELR* as the content predictor for enhancing user-based CF. Usenet news filtering system [65] uses filterbots as additional participants in a user-based CF community. The filterbot framework provides an augmentation that should improve the value of collaborative filtering systems. Fab [61] is a meta-level and cascade hybrid system which maintains user profiles of interest using relevance feedback technique, and uses user-based CF to identify similar profiles for making recommendations. Pazzani [66] employed a meta-level approach called “collaboration via content” which measures similarity between users on the content-based profile built by Winnow algorithm. Similarly, Schwab et al. [67] used instance-based learning to create content-based user profiles and then employed the Pearson correlation for measuring the similarity between users’ profiles.

Item-based CF: The queveo.tv system [68] is a TV program recommender system that combines CB and item-based CF in a mixed manner.

Model-based CF: Basu et al. [69] combined collaborative and content features in a single rule-based classifier. de Campos et al. [70] presented an augmentation approach based on Bayesian networks which uses probabilistic reasoning to compute the probability distribution over the expected rating. Their approach could also be classified as “mixed” since there is a mechanism to control the contribution of both CF and CB elements. Condliff et al. [71] proposed a meta-level hybrid approach based on Bayesian mixed-effects regression model that incorporates all the available information in a single unified framework.

6.2. Combining CF with DM

Integrating CF with DM recommendations can reduce sparsity problem of CF. It can also cope with new user problem since DM does not require a list of ratings from the user. Some researches that have used this approach are as follows:

User-based CF: The most of the previous researches in this area can be classified as a feature combination hybrid [4], [42], [43]. In these systems, demographic and rating similarity weights between users are combined in order to predict item ratings. Furthermore, Song et al. [72] proposed a hybrid recommender algorithm by an improved similarity method, combining demographic recommendation techniques and user-based CF algorithms.

Item-based CF: Xia et al. [73] presented an augmentation hybrid approach, which utilizes user's demographic information in order to impute the missing data. Vozalis and Margaritis [4], [74] proposed feature combination hybrid algorithms in which demographic and rating correlations are combined in order to enhance item-based CF.

To the best of our knowledge, no previous work attempts to combine model-based CF with demographic recommendations.

6.3. Combining CF with KB

The possibility of such combination is introduced in [75]. It will avoid the disadvantages of a CF recommender, such as such as new user/item problem, sparsity, gray sheep, the requirement to be initialized with a large database of users' ratings, and the possibility to generate invalid recommendations when a user's interests change. However, this system requires knowledge engineering with all of its attendant difficulties [76].

Previous works in this area are limited to the hybridization of user-base CF with knowledge-based recommendations. Such hybrid systems including:

User-based CF: Towle and Quinn [77] proposed a weighted hybrid approach based around explicit models of both products and customers, along with an intelligent system which performs a mapping between the two. Tran and Cohen [76] presented a switching hybrid system that uses an interactive interface agent for selecting the appropriate subsystem (KB or user-based CF), coordinating the operations of the two subsystems and interacting with users in uncertain situations. EntreeC [2] is a cascade system in which KB techniques are used to boot strap the user-based CF engine while its data pool is small, and the user-based CF is used as a post filter for the KB recommender.

6.4. Combining CF with SB

Traditional CF does not consider the semantic relationship between different items or users, thus recommendation quality is poor. Combining semantic similarity and rating similarity between items provides two primary advantages over pure CF. First, the semantic attributes for items allows the system to make inferences based on the underlying reasons for which a user may or may not be interested in a particular item. Secondly, in the case of new item or in very sparse data sets, the system can still use the semantic information to provide reasonable recommendations for users [49]. Also, semantic knowledge about the user preferences helps to provide proper recommendations for new or gray sheep users. Some of these systems include:

User-based CF: Ceylan and Birturk [78] used semantic similarities between items to convert a sparse ratings matrix into a full ratings matrix; and then used user-based CF to provide recommendations. Lops et al. [9] augmented user-based CF through semantic user profiles which are learnt by a relevance feedback algorithm from sense-represented documents. Blanco-Fernández et al. [79] extended the "collaboration via content" paradigm, but they reasoned about the semantics of the preferences instead of using only the content descriptions. Similarly, Sieg et al. [80] proposed a meta-level approach in which the ontological user profiles are exploited to form semantic neighborhoods. The predictions are computed as the weighted average of deviations from the neighbor's mean using the similarity between profiles as the weight.

Item-based CF: MC-SeCF approach [47] uses the weighted harmonic mean for integrating the separate predictions from the enhanced multi criteria item-based CF and the item-based semantic filtering module. The latter module combines the overall rating with semantic similarity between items. Hu and Zhou [81] proposed an approach which uses content semantic similarities of items to augment existing user data, and then provides personalized recommendations through item-based CF. In the approach presented by Mobasher et al. [49], a single prediction algorithm is provided with linear combination of semantic and item rating similarity. Jin and Mobasher [82] presented two algorithms which use semantic similarity to enhance item-based CF. In the first algorithm, they combined the semantic and rating similarities and used the combined similarity to generate predictions. In the second algorithm, they used the combined similarity for predicting the missing ratings, and then they run the first algorithm on this less sparse ratings matrix.

To the best of our knowledge, there is no previous work that combines model-based CF with semantic-based recommenders.

6.5. Combining CF with CA

Collaborative approaches may provide poor recommendations since they do not consider the discrepancies introduced by the context. Such hybrid system can make recommendations that best match with users' preferences and needs at the right moment and in the right place. Adomavicius and Tuzhilin [83] presented three different approaches for incorporating contextual information into recommendation process: pre-filtering, post-filtering and contextual modeling. Pre-filtering is a feature augmentation method in which contextual information is used for the selection of the most relevant data for generating recommendations. Post-filtering uses cascade architecture and re-ranks the recommendation list depending on the current context. Contextual modeling can be classified as a feature combination which uses contextual information directly in the modeling technique. Some context-aware recommenders using CF are as follows:

User-based CF: Smart Radio [84] is a music playlist recommender that uses user-based CF as its primary recommendation strategy and then refines these recommendations based on similarity to the current context. Chen [85] proposed a system where a single prediction algorithm combines rating similarity between active user and his neighbors with ratings which are weighted using the context similarity. The context-aware travel recommendation system proposed by Zheng et al. [86] is a hybrid of contextual pre-filtering and contextual modeling. This system consists of three components where the first one implements pre-filtering and the others incorporate contextual data into the process of modeling.

Item-based CF: Tan and Pan [87] introduced a feature augmentation approach which first calculates the rating of the users for the items in the current context using context similarity. Then, it utilizes these ratings in order to form the neighborhood of the active item using Pearson correlation for generating the prediction. Their approach also can be classified as feature combination since it builds a user × item × context model for incorporating contextual information.

Model-based CF: Karatzoglou et al. [88] introduced a CF based on tensor factorization that allows for a generic integration of contextual information by modeling the data as a user-item-context n-dimensional tensor. Oku et al. [89] also presented a contextual modeling approach in which the functionality of a Support Vector Machines is extended by adding axes of context to the feature space in order to consider the users' context.

6.6. Combining CF Algorithms

The two major classes of *CF* approaches, memory-based and model-based *CF* approaches, can be combined to take the advantage of accuracy in the former method as well as the scalability of the latter. Also in some researches, user-based and item-based CF is combined in order to cope with sparsity and provide better recommendation quality.

Combining memory-based and model-based CF: Xue et al. [33] clustered the user data and applied intra-cluster smoothing to reduce sparsity. The use of clusters for smoothing permits the integration of the advantages from both the memory-based and model-based approaches. Chuan et al. [90] used item-based CF in order to augment users rating data and then applied the user-based classified regression model to this augmented dataset. Moghaddam and Selamat [91] clustered the users based on their demographic information, then partitioned rating data based on these clusters and apply user-based CF on each partition separately. Wang et al. [92] proposed a combination filtering method which firstly constructs a user model off-line. Then, it forms the neighbor set based on the model and makes on-line recommendation using memory-based CF. Zhang et al. [93] proposed an efficient collaborative approach using smoothing and fusing strategies. Their approach clusters users with a smoothing strategy to eliminate the diversity in user ratings styles. Then, it fuses different rating sources for producing recommendations. Sun et al. [94] proposed a novel hybrid framework for CF which combines memory-based and model-based approaches as the first step and takes full use of users, items and rating information via a fusion mechanism as the second step.

Combining User-based CF and Item-based CF: Li et al. [32] used a set of similar items to the target item (similar items are obtained from item-based CF) as input to a user-based system. Then, this user-based system determines the neighbors of active user based on this set. Ma et al. [31] linearly combined the predictions of the user-based and item-based CF for augmenting the rating data. Then, they predicted ratings for the active users using the prediction process which is similar to the augmentation process. Ji et al. [95] integrates two algorithms into a unified framework by a weighted sum of the combination of item neighbor's ratings and of user neighbor's ratings.

Table 1 shows the summary of previous works related the different categories of discussed hybrid CF systems. Also, we have indicated the domain in which the recommender is experimented. In this table, the dark cells indicate the hybridization method(s) which is/are employed in each work.

Table 1. Classification of hybrid CF systems

Hybrid of CF with	Type of CF	Hybridization Method							Related Works	Domain of Experiment
		Weighted	*Mixed*	*Switching*	*Feature combination*	*Cascade*	*Feature augmentation*	*Meta-level*		
Content-based	*UB*	■							[39]	Online newspaper
			■						[62]	TV programs
						■		■	[61]	Web pages
							■		[63], [64], [65]	Movie dataset
								■	[66]	Restaurants
								■	[67]	Research funding
	IB		■						[68]	TV programs
	Model-based				■				[69]	Movie dataset
			■				■		[70]	
								■	[71]	Movies & beverages data
Demographic	*UB*				■				[4], [42], [72]	Movie data
					■				[43]	Music suggestion
	IB						■		[73]	Movie dataset
					■				[4], [74]	
Knowledge -based	*UB*	■							[77]	Not tested
				■					[76]	
						■			[2]	Restaurants
Semantic-based	*UB*						■		[9], [78]	Movie dataset
								■	[79]	TV programs
								■	[80]	Book dataset
	IB	■							[47]	Movie dataset
					■				[49]	Movie rating & Real Estate Usage data
					■				[82]	Movie data
							■		[81], [82]	Movie dataset
Context-Aware	*UB*					■			[84]	Music playlist
					■	■			[86]	Travel
					■				[85]	Not tested
	IB				■		■		[87]	Movie dataset
	Model-based				■				[88]	Movie & food ratings
					■				[89]	Restaurants
Collaborative	*Memory -based and Model-based*						■		[33], [90]	Movie dataset
						■			[91]	
					■				[92]	
					■		■		[93]	
		■			■		■		[94]	
	UB / IB	■					■		[31]	Movie dataset
							■		[32]	
		■							[95]	

7. Comparison of the Hybrid CF Systems

In previous section, we distinguished different categories of the hybrid CF systems, including hybrid of CF with: CB, DM, KB, SB, CA and hybrid systems combining CF algorithms. In each category, a particular CF algorithm (memory- or model-based) is combined with another approach in order to avoid limitations of that particular CF algorithm. In this section, we investigate the performance of each hybrid system in dealing with the main limitations of collaborative part of the system. All hybrid CF systems have strengths and weaknesses discussed below and summarized in Table 2.

The hybrid between memory-based CF and CB helps to avoid the new item and sparsity problems. Content-based profiles can also reduce the gray sheep problem in both case of memory- or model-based CF. In dealing with these problems, CB predictor of the system can generate proper recommendations based on items similar to the ones that each user liked in the past. But, the new user problem of memory-based CF still remains because it is also a main limitation of CB predictor. Also, due to the syntactic nature of CB predictor, the diversity of the recommendations is not high.

Combining CF with demographic data improves the quality of collaborative recommendations. Demographic data alleviates the new user problem of CF. In the case of new user, DM predictor of the system can generate proper recommendations because it does not require a list of ratings from the user. As mentioned earlier, DM predictor also suffers from gray ship and new item problems. So, these problems cannot be solved in these hybrid systems. Moreover, demographic data is usually difficult to obtain. With sensitivity to on-line privacy increasing, demographic data is likely to be information that users are reluctant to disclose [2].

The hybridization of CF with KB or SB reduces common limitations associated with each kind of CF. These systems explore extensively the knowledge base and discover the hidden relationship between different items or users. Such relationships provide the knowledge missed by the other approaches and permit to generate reasonable recommendations in sparse data sets or in the case of new user/item and gray sheep users/items. As mentioned earlier, SB systems are a special kind of KB systems. SB systems use Semantic Web technologies which provide machine-readable knowledge and improve knowledge representation compare to the other KB systems. So, the hybridization of CF with SB predictor has a significant advantage that improves the overall quality of recommendations. Also, SB systems increase the diversity of the recommendations because they recommend items semantically associated with user preferences. Such associations allow to discover that some items are appealing to the user even though they do not share the features defined in user profile [41]. The drawback of CF/SB and CF/KB systems is the need for knowledge engineering.

The main advantage of Combining CF with CA is the ability to generate valuable collaborative recommendations at the right moment, in the right place and on the right media. The sparsity, cold start and gray sheep problems are not resolved in these hybrid systems.

The integration of memory- and model-based approaches takes the advantage of accuracy in the memory-based as well as the scalability of the model-based method. In these systems, the

Table 2. Comparison of the different hybrid CF systems

Hybrid of CF with	Type of CF	Strengths	Weaknesses
Content-based	*Memory-based*	• Reducing new item problem • Reducing sparsity problem • Reducing gray sheep problem • Higher accuracy than pure memory-based CF	• New user problem • Unscalable for large datasets • Diversity of the recommendations is not high
	Model-based	• Reducing gray sheep problem • Improving prediction accuracy over pure model-based CF • scalable	• Lower accuracy compared to hybrid of memory-based CF with CB • Diversity of the recommendations is not high
Demographic	*Memory-based*	• Alleviating the new user problem • Higher accuracy than pure memory-based CF	• Demographic data is difficult to obtain • Unscalable for large datasets • Gray sheep problem
	Model-based	• Improving prediction accuracy over pure model-based CF • scalable	• Demographic data is difficult to obtain • Gray sheep problem • Lower accuracy compared to hybrid of memory-based CF with DM
Knowledge-based	*Memory-based*	• Reducing cold start problem • Reducing sparsity problem • Reducing gray sheep problem • Higher accuracy than pure memory-based CF • Responding quickly to the changes of user's preference	• Unscalable for large datasets • Knowledge engineering
	Model-based	• Reducing gray sheep problem • Improving prediction accuracy over pure model-based CF • scalable • Responding quickly to the changes of user's preference	• Knowledge engineering • Lower accuracy compared to hybrid of memory-based CF with KB
Semantic-based	*Memory-based*	• Reducing cold start problem • Reducing sparsity problem • Reducing gray sheep problem • Higher accuracy than pure memory-based CF • Responding quickly to the changes of user's preference • Higher diversity of the recommendations	• Unscalable for large datasets • Knowledge engineering
	Model-based	• Reducing gray sheep problem • Improving prediction accuracy over pure model-based CF • scalable • Responding quickly to the changes of user's preference • Higher diversity of the recommendations	• Knowledge engineering • Lower accuracy compared to hybrid of memory-based CF with KB
Context-Aware	*Memory-based*	• Generating valuable recommendations in dynamic environments	• Cold start problem • Sparsity problem • Gray sheep problem • Unscalable for large datasets
	Model-based	• Generating valuable recommendations in dynamic environments • scalable	• Gray sheep problem • Lower accuracy compared to hybrid of memory-based CF with CA
Collaborative	*Memory- and Model-based*	• Reducing sparsity and cold start problem of memory-based CF • Improving scalability of memory-based CF • Improving accuracy of model-based CF	• Gray sheep problem
	UB / IB	• Reducing sparsity problem • Alleviating cold start problem • Higher accuracy	• Gray sheep problem • Unscalable for large datasets

sparsity and cold start problems of memory-based CF are somewhat reduced. However, they have increased complexity and are expensive to implement [96]. Also, gray sheep problem still remains in these hybrid systems. Finally, the hybridization of UB and IB approaches helps to reduce the sparsity problem of each individual approach. In both cases of UB and IB, only partial information from the data in the user-item matrix is employed to predict unknown ratings. UB uses ratings of the target item by similar users; and IB uses ratings of similar items by the active user.

UB/IB hybrid systems combine predictions from these two sources and therefore they are more robust against data sparsity. With reducing the sparsity, cold start problem is also alleviated. The other limitations related to UB and IB methods are not resolved in these hybrid systems.Table 2 summarizes the strengths and weaknesses of each hybrid CF system.

8. Conclusion

Collaborative filtering is one of the most successful recommender techniques. There are two general classes of CF algorithms. Memory-based algorithms operate over the entire rating matrix to generate recommendations. Memory-based algorithms suffer from sparsity, cold start and scalability problems. To overcome shortcomings of memory-based CF, model-based algorithms have been investigated. Model-based algorithms use the rating matrix to learn a model, which is then used for predictions. The sparsity and cold start problem are somewhat reduced in model-based algorithms. Model-based approaches improve system scalability at the expense of accuracy.

Hoping to avoid the main limitations of CF algorithms, hybrid systems have been emerged that combine CF with other recommendation approaches. In this paper, we classified hybrid CF systems into different categories and reviewed the previous works related to each category. These categories include combination of memory- or model-based CF with: content-based, demographic, knowledge-based, semantic-based or context-aware approaches. Furthermore, memory-based and model-based algorithms can be combined to form another type of hybrid CF systems. After classifying hybrid CF systems, we compared their performance and indicated their strengths and weaknesses.

Among the existing hybrid CF systems, hybrid of CF with sematic-based approach has more advantages. It reduces the main limitations associated with CF, responds to the user's immediate preferences and provides recommendations with high diversity. Semantic Web technologies have revolutionized the way that systems integrate and share data. These technologies are becoming increasingly important for developing knowledge management systems. In recent years, many recommender systems have begun to employ semantic technologies in order to improve theirs mechanisms of recommendation. Semantic knowledge based systems can reinforce the collaborative recommendations and avoid the problem known as sparsity, cold start and gray sheep. So, the hybridization of semantic with collaborative filtering seems more relevant than the others. Also, we believe that incorporating contextual information in CF/SB systems brings the additional advantage of adjusting recommendations in dynamic environments.

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