Recommender System Application Developments: A Survey

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Abstract

A recommender system aims to provide users with personalized online product or service recommendations to handle the increasing online information overload problem and improve customer relationship management. Various recommender system techniques have been proposed since the mid-1990s, and many sorts of recommender system software have been developed recently for a variety of applications. Researchers and managers recognize that recommender systems offer great opportunities and challenges for business, government, education, and other domains, with more recent successful developments of recommender systems for real-world applications becoming apparent. It is thus vital that a high quality, instructive review of current trends should be conducted, not only of the theoretical research results but more importantly of the practical developments in recommender systems. This paper therefore reviews up-to-date application developments of recommender systems, clusters their applications into eight main categories: e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services and e-group activities, and summarizes the related recommendation techniques used in each category. It systematically examines the reported recommender systems through four dimensions: recommendation methods (such as CF), recommender systems software (such as BizSeeker), real-world application domains (such as e-business) and application platforms (such as mobile-based platforms). Some significant new topics are identified and listed as new directions. By providing a state-of-the-art knowledge, this survey will directly support researchers and practical professionals in their understanding of developments in recommender system applications.

Keywords: Recommender systems, e-service personalization, e-commerce, e-learning, e-government

1 Introduction

Recommender systems can be defined as programs which attempt to recommend the most suitable *items* (products or services) to particular *users* (individuals or businesses) by predicting a user's interest in an item based on related information about the items, the users and the interactions between items and users [1]. The aim of developing recommender systems is to reduce information overload by retrieving the most relevant information and services from a huge amount of data, thereby providing personalized services. The most important feature of a recommender system is its ability to "guess" a user's preferences and interests by analyzing the behavior of this user and/or the behavior of other users to generate personalized recommendations [2].

E-service personalization techniques are typified by recommender systems, which have gained much attention in the past 20 years [3]. Early research in recommender systems grew out of information retrieval and filtering research [4], and recommender systems emerged as an independent research area in the mid-1990s when researchers started to focus on recommendation problems that explicitly rely on the rating structure [3]. Commonly used recommendation techniques include collaborative filtering (CF) [5], content-based (CB) [6] and knowledge-based (KB) [7] techniques. Each recommendation approach has advantages and limitations; for example, CF has sparseness, scalability and cold-start problems [3, 5], while CB has overspecialized recommendations [3]. To solve these problems, many advanced recommendation approaches have been proposed, such as social network-based recommender systems [8], fuzzy recommender systems [9, 10], context awareness-based recommender systems [11] and group recommender systems [12].

With the development of recommendation approaches and techniques, more and more recommender systems (software) have been implemented and many real-world recommender system applications have been developed. It was pointed out recently that application study is the main research focus of current recommender system research, especially in the current age of big data [1, 13]. The applications of recommender systems include recommending movies, music, television programs, books, documents, websites, conferences, tourism scenic spots and learning materials, and involve the areas of e-commerce, e-learning, e-library, e-government and e-business services. Therefore, to help researchers understand the recommender system development experience and to assist developers to approve applicable systems development in practice, this paper reviews the latest recommender systems (software) that have been developed using assorted techniques in a range of application fields. We cluster recommender system applications into eight main domains: e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services and e-group activities. The most typical recommender systems in each application domain are presented and analyzed, and the relevant recommendation techniques used in the application domain are identified.

Several survey papers on recommender systems have been published in the last few years. However, these papers focus on either recommendation techniques and approaches or a specific domain of recommender system development; none of these survey papers focuses on the comprehensive analysis of recommender system applications. For example, the paper by Adomavicius and Tuzhilin [3] presented an overview of content-based, collaborative filtering-based, and hybrid recommendation approaches. It describes the various limitations of these recommendation approaches and discusses possible extensions that could improve recommendation capabilities. Bobadilla et al. [1] reviewed fundamental recommendation, evaluation, social filtering, and group recommendation techniques, as well as several recently-developed techniques such as the location-aware and bio-inspired recommendation techniques. Park et al. [13] reviewed 210 papers on recommender system areas and classified them by the journal and year of publication, their application fields, and their data mining techniques. Burke [14] surveyed the landscape of actual and possible hybrid recommender systems. The paper compares recommendation techniques and reviews hybridization methods. Lü et al. [15] reviewed recommendation algorithms, focusing on a careful explanation of how the most frequently-used algorithms in recommender systems work. They also presented the basic concepts of CF and their evaluation metrics, dimensionality reduction techniques, diffusion-based methods, social filtering and meta approaches. In addition, there are recommender system survey papers on specific application domains, such as e-commerce recommender systems [16, 17] and e-learning recommender systems [18]. We would point out that although several recommender system survey papers have been published in recent years, no research work, to the best of our knowledge, has been conducted to comprehensively review recommender system applications, while the study of recommender system applications is a very significant issue for both researchers and real-world developers in this area.

There are two main types of article being reviewed in this survey: Type 1 — articles on recommendation techniques (including related methods and approaches) and Type 2 — articles on recommender system applications (including related software and case studies). The search and selection of these articles were performed according to the following four steps:

Step 1. Publication database identification and determination

The following publication databases were searched to provide a comprehensive bibliography of research papers on recommender systems: Science Direct, ACM Digital Library, IEEE Xplore and SpringerLink.

Step 2. Preliminary screening of Type 2 articles

The search was first performed based on related keywords of recommender system applications. The articles were then selected as references if they satisfied one of the following criteria: 1) present recommender system development in software; 2) report a recommender system framework of a specific application; 3) provide a real-world recommender system application. Following this process, selected articles were used as the preliminary references for this study.

Step 3. Result filtering for Type 2 articles

The keywords of the preliminary references were extracted and clustered manually. Based on the keywords related to application domain, these papers were divided, using "topic clustering", into eight groups (application domains): e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services and e-group activities. Each domain has a reference list. The references in each application domain were filtered again to keep only the latest, highly innovative, high impact articles. This article selection process was based on the following criteria: 1) publication time — published within the last 24 months; 2) impact — published in high quality (high impact factor) journals, or in conference proceedings or book chapters but with high citations[1]; 3) coverage — reported a new or particular application domain; 4) typicality — only the most typical examples relating to similar applications were retained, in line with criteria 1) and 2). After completing this process, 104 research articles were selected as references.

Step 4. Type 1 article selection

The recommendation techniques applied in the above-mentioned eight application domains were analyzed, including traditional methods such as collaborative filtering-based, content-based, knowledge-based, and recently developed advanced recommendation methods, such as fuzzy set-based, social network-based, trust-based, context awareness-based, and group recommendation approaches. For each recommendation technique category, relevant research papers were carefully searched and reviewed. These papers were also selected according to the two criteria: 1) publication time; 2) impact. These types of article are mainly used in Section 2.

Ultimately, 177 articles in total were selected as the final reference list for this paper.

The main contributions of this paper are:

1) recommender systems arose from practical requirements as personalized e-services are required in many application domains, but existing recommender system surveys mainly focus on recommendation theories and approaches. This paper surveyed the recommender systems from the requirements of each application domain, which complements the existing recommender system surveys and provides useful guide for industrial practitioners and researchers;

2) this paper comprehensively and perceptively summarizes research achievements on recommender systems from the point of view of "system", and strategically clusters the recommender system applications into eight application domains, which provides a framework for recommender system development;

[1] "high citation" means that the citation of the paper is greater than the average citation rates listed in the "ISI Web of Knowledge – Essential Science Indicators", and the citation per year of the paper is larger than 1.

3) for each application domain, it carefully analyses typical recommender system frameworks and effectively identifies the specific requirements for recommendation techniques in the domain. This will directly motivate and support researchers and practitioners to promote the popularization and application of recommender systems in different domains;

4) it uncovers several very new recommendation techniques, such as the social network-based and context awareness-based recommendation technique, and reveals their successful application domains;

5) most importantly, it systematically examines the reported recommender systems through four dimensions: recommendation methods (such as CF), recommender systems software (such as BizSeeker), real-world application domains (such as e-business) and application platforms (such as mobile-based and TV-based platforms);

6) it particularly suggests several very innovative emerging research topics/directions in the area of recommender systems.

The remainder of this paper is structured as follows. In Section 2, the recommendation techniques are reviewed and analyzed. Sections 3 to 10 respectively present the eight main application domains of recommender systems. Section 11 presents our four-dimensional comprehensive analysis and main findings.

2 Recommendation techniques

To understand and analyze the application developments of recommender systems, this section first reviews the main recommendation techniques, including traditional methods such as collaborative filtering-based, content-based, knowledge-based, and hybrid methods [14], and recently developed advanced methods, such as fuzzy set-based, social network-based, trust-based, context awareness-based, and group recommendation approaches.

2.1 Content-based recommendation techniques

Content-based (CB) recommendation techniques recommend articles or commodities that are similar to items previously preferred by a specific user [6]. The basic principles of CB recommender systems are: 1) To analyze the description of the items preferred by a particular user to determine the principal common attributes (preferences) that can be used to distinguish these items. These preferences are stored in a user profile. 2) To compare each item's attributes with the user profile so that only items that have a high degree of similarity with the user profile will be recommended [6].

In CB recommender systems, two techniques have been used to generate recommendations. One technique generates recommendations heuristically using traditional information retrieval methods, such as cosine similarity measure. The other technique generates recommendations using statistical learning and machine learning methods, largely building models that are capable of learning users' interests from the historical data (training data) of users.

2.2 Collaborative filtering-based recommendation techniques

Collaborative filtering (CF)-based recommendation techniques help people to make choices based on the opinions of other people who share similar interests [19]. The CF technique can be divided into user-based and item-based CF approaches [20]. In the user-based CF approach, a user will receive recommendations of items liked by similar users. In the item-based CF approach, a user will receive recommendations of items that are similar to those they have loved in the past. The similarity between users or items can be calculated by

Pearson correlation-based similarity [21], constrained Pearson correlation (CPC)-based similarity, cosine-based similarity, or adjusted cosine-based measures. When calculating the similarity between items using the above measures, only users who have rated both items are considered. This can influence the similarity accuracy when items which have received a very small number of ratings express a high level of similarity with other items. To improve similarity accuracy, an enhanced item-based CF approach was presented by combining the adjusted cosine approach with Jaccard metric as a weighting scheme. To compute the similarity between users, the Jaccard metric was used as a weighting scheme with the CPC to obtain a weighted CPC measure [22]. To deal with the disadvantage of the single-rating based approach, multi-criteria collaborative filtering was developed [23].

2.3 Knowledge-based recommendation techniques

Knowledge-Based (KB) recommendation offers items to users based on knowledge about the users, items and/or their relationships. Usually, KB recommendations retain a functional knowledge base that describes how a particular item meets a specific user's need, which can be performed based on inferences about the relationship between a user's need and a possible recommendation [14]. Case-based reasoning is a common expression of KB recommendation technique in which case-based recommender systems represent items as cases and generate the recommendations by retrieving the most similar cases to the user's query or profile [24]. Ontology, as a formal knowledge representation method, represents the domain concepts and the relationships between those concepts. It has been used to express domain knowledge in recommender systems [25]. The semantic similarity between items can be calculated based on the domain ontology [26].

2.4 Hybrid recommendation techniques

To achieve higher performance and overcome the drawbacks of traditional recommendation techniques, a hybrid recommendation technique that combines the best features of two or more recommendation techniques into one hybrid technique has been proposed [27]. According to Burke [27], there are seven basic hybridization mechanisms of combinations used in recommender systems to build hybrids: weighted [28], mixed [29], switching [30], feature combination, feature augmentation [31, 32], cascade [14] and meta-level [33]. The most common practice in the existing hybrid recommendation techniques is to combine the CF recommendation techniques with the other recommendation techniques in an attempt to avoid cold-start, sparseness and/or scalability problems [3, 34].

2.5 Computational intelligence-based recommendation techniques

Computational intelligence (CI) techniques include Bayesian techniques, artificial neural networks, clustering techniques, genetic algorithms and fuzzy set techniques. In recommender systems, these computational intelligence techniques are widely used to construct recommendation models.

A Bayesian classifier is a probabilistic methodology for solving classification problems. Bayesian classifiers are popular for model-based recommender systems [35] and are often used to derive the model for CB recommender systems. When a Bayesian network is implemented in recommender systems, each node corresponds to an item, and the states correspond to each possible vote value. In the network, there will be a set of parent items for each item which represent its best predictors. A hierarchical Bayesian network has also been introduced as a framework for combining both CB and CF approaches [36].

An artificial neural network (ANN) is an assembly of inter-connected nodes and weighted links that is inspired by the architecture of the biological brain and can be used to construct model-based recommender systems [35]. Hsu et al. [37] used ANN to construct a TV recommender system, using the back-propagation neural network method to train a three-layered neural network. A hybrid recommender system combining CB and CF was proposed by Christakou et al. [38] to generate precise recommendations for movies. The content filtering part of the system is based on a trained ANN representing individual user preferences.

Clustering entails the assignment of items to groups so that items in the same group are more similar than the items in different groups. Clustering can be used to reduce the computation cost for finding the *k*-nearest neighbors, for instance in [35]. Xue et al. [39] presented a typical use of clustering in recommender systems. Their method uses the clusters for smoothing the unrated data for individual users. The unrated items of an individual user in a group can be predicted by use of the rating information from a group of closely related users. Moreover, assuming that the nearest neighbor should also be in the Top N most similar clusters to the active user, only the nearest neighbours in the Top N clusters need to be selected, which enables the system to be scalable. The clustering technique is also used to address the cold start problem in recommender systems by grouping items [40]. Ghazanfar and Prügel-Bennett [41] used clustering algorithms to identify and solve the gray-sheep users problem.

Genetic algorithms (GA) are stochastic search techniques which are suitable for parameter optimization problems with an objective function subject to hard and soft constraints [42]. They have mainly been used in two aspects of recommender systems [43]: clustering [42] and hybrid user models [44]. GA-based K-means clustering is applied to a real-world online shopping market segmentation case for personalized recommender systems in [42], resulting in improved segmentation performance. A genetic algorithm method is presented for obtaining optimal similarity functions in [43]. The results show that the obtained similarity functions provide better quality and faster results than those provided by traditional metrics.

Fuzzy set theory offers a rich spectrum of methods for the management of non-stochastic uncertainty. It is well suited to handling imprecise information, the un-sharpness of classes of objects or situations, and the gradualness of preference profiles [45]. In [46], an item in a recommender system was represented as a fuzzy set over an assertion set. The value of a feature or attribute for an item is a fuzzy set over the subset of the assertions relevant to the feature. The user's intentional preferences are represented as a basic preference module, which is the ordered weighted averaging of components that can evaluate items. The user's extensional preferences are expressed as a fuzzy set over the user's experienced items whose membership degrees are the ratings. Based on the representation, the preference for an item by a user can be inferred. In [45, 47], a feature set for items and a set of values for each feature are defined. The items are represented as the fuzzy subset over the values, denoted by a feature vector. Cao and Li [48] used linguistic terms for domain experts to evaluate the features of consumer electronic products and allow users to use linguistic terms to express their needs for item features. In [49], the user preferences are represented as two fuzzy relations, positive and negative feelings, from user set to item set. The item similarity is computed by integrating CB similarity, which is a fuzzy relation within an item set, and item-based CF similarity, which is computed on the basis of user preferences. The user similarity is generated by fuzzy relational calculus from the preferences and item similarity relations. The final recommendations, which are the positive and negative preferences, are generated by composing the above fuzzy relations. Porcel et al. [50] developed a fuzzy linguistic-based recommender system combining CB filtering and the multi-granular fuzzy linguistic modeling technique, which is useful for assessing different qualitative concepts. Zhang et al. [9] used fuzzy set techniques to deal with linguistic ratings and calculate the fuzzy CF similarities, to provide a solution for handling uncertainty in a telecom product/service recommendation process.

2.6 Social network-based recommendation techniques

Social network analysis (SNA) has been used in recommender systems as a result of the dramatic growth of social networking tools in Web-based systems in recent years. To help improve user experience, recommender systems increasingly provide users with the ability to engage in social interaction with other users, such as online friending, making social comments, social tags, etc. These trends offer opportunities for making recommendations by utilizing users' social ties, especially for systems whose rating data is too sparse to conduct collaborative filtering.

"Trust" is a widely discussed relationship in social network studies. Considering the real world situation in which one's decision to purchase is more likely to be influenced by suggestions from friends than by website advertising, a user's social network may be an important source if it exists in a recommender system. Likewise, due to the inability of standard CF approaches to find sufficient similar neighbours in sparse data sets, users' social relationships are emerging as another improvement facet for recommender systems. Trust represents an intuitive opinion to other users. In a recommender system, the word "trust" is usually defined as "how well does Alice trust Bob concerning the specific product or taste" [51]. It has been proven that there is positive correlation between trust and user similarity in online communities [52]. Researchers have conducted series of studies on integrating trust into recommender systems. These trust-based frameworks are usually based on analyses of the propagation mechanism of "the Web of trust" of users. In the trust metric module of Massa and Avesani [53], the undefined trust value was roughly predicted based on an assumption that "users closer in the trust network to the source user have higher trust value". A systematic algorithm, TidalTrust, was proposed by Golbeck [54] to address the trust-based rating prediction problem and is considered to be effective in the forming process of numeric trust networks in several systems. Ben-Shimon et al. [51] constructed personal social trees for active users by using a Breadth-First Search algorithm and then computed the distances from active users to others, which can be seen as a reflection of trust, as the final rating prediction weights. In [55], the authors analysed the local trust matrix and global trust matrix respectively in a recommender system. Their results indicate that both local trust-awareness and global trust-awareness (also known as reputation) can stimulate increases in recommendation coverage and accuracy. Typically, trust-based approaches are thought to be able to increase recommendation coverage by maintaining accuracy.

Other than trust, a massive number of other types of social relations are being utilized for recommendation generation. For example, social bookmarks [56], physical context [57], social tags [58], "co-authorship" relations [59], and more have recently been utilized as substitutes for the trust or similarity metric for filtering and predicting a user's preference. Shiratsuchi et al. [56] developed an online information recommender system based on a "co-citation" network of online bookmarking, in which the number of "co-cited" bookmarks is treated as the weight of social relations. Woerndl and Groh [57] extracted the entire relevant social context as a vector and integrated it into rating data to generate a multi-dimensional user-item-context matrix for generating personal recommendations in a particular environment. In [58], Ma et al. attempted to combine a probabilistic matrix factorization method and social context/trust information for recommendation making. In the work of [59] concerning the recommendation of academic activities, a social relation is represented by the notion "co-authorship": "the times two researchers have co-authored papers".

Researchers have also conducted several studies on the social networks of recommender systems based only on the user-item rating matrix. Palau et al. [60] structured social networks to present the collaborative relationships and proposed several measures to explain how collaboration is achieved in the recommendation framework. O'Donovan [61] claimed that user similarity may be overemphasized. They presented a trust calculation model from rating data in their trust-based recommendation architecture to make the system more explainable without decreasing prediction accuracy.

2.7 Context awareness-based recommendation techniques

One of the most cited definitions of context is the definition of Dey et al. [62] that defines context as "any information that can be used to characterize the situation of an entity. An entity could be a person, a place, or an object that is considered relevant to the interaction between a user and an application, including the user and the application themselves." The context information such as time, geometrical information, or the company of other people (friends, families or colleagues for example) has been recently considered in existing recommender systems; for example, the information obtained with the rapid growth of mobile handset use [63]. The contextual information provides additional information for recommendation making, especially for some applications in which it is not sufficient to consider only users and items, such as recommending a vacation package, or personalized content on a website. It is also important to incorporate the contextual information in the recommendation process to be able to recommend items to users in specific circumstances. For example, using the temporal context, a travel recommender system might make a very different vacation recommendation in winter compared to summer [64]. The contextual information about users in technology enhanced learning environments is also incorporated into the recommendation process [65].

In the review of Adomavicius and Tuzhilin [11], context in the recommender system field is a multifaceted concept used across various disciplines, with each discipline adopting a certain angle and putting its "stamp" on this concept. With context awareness, the rating function is no longer a two-dimensional (2D) function (R: $User \times Item \rightarrow Rating$) but becomes a multi-dimensional function (R: $User \times Item \times Context \rightarrow Rating$), where *User* and *Item* are the domains of users and items respectively, *Rating* is the domain of ratings, and *Context* specifies the contextual information associated with the application. To incorporate the contextual information in recommender systems, Adomavicius and Tuzhilin [11] proposed a three-step process to make such information computable and valuable: Contextual Pre-Filtering, Contextual Post-Filtering, and Contextual Modeling. By processing all three steps, the system can detect the contextual information that is useful and compliable for making suggestions.

2.8 Group recommendation techniques

Group recommender systems (GRS) are proposed to produce a group of user suggestions when group members are unable to gather for face-to-face negotiation, or their preferences are not clear in spite of meeting each other [66, 67]. GRS are also called e-group activity recommender systems, and have been applied to many domains including movies, music, webpages, events and complex issues such as travel plans. Many strategies, inspired by social choice theory and decision-making procedure, are used for aggregating all the members into a group. Masthoff [12] summarized eleven strategies including least misery, average, most pleasure and their adaptations, as the most common in GRS. Quijano-Sanchez et al. [68] used average strategy; PolyLens [69] used the least misery strategy [70]; MusicFX used a variant of the average without misery strategy; and Popescu [71] adopted the voting mechanism. Other strategies, like approval voting and sum, are also used in aggregation. Except for the aggregating methods, asynchronous and synchronous communications are also involved in GRS for multi-user support. In [72], an asynchronous communication mechanism for users was developed in which users in a group can view (and also copy) other members' choices. McCarthy et al. [73] implemented a synchronous conversational system to produce ski holiday suggestions for groups. The features predefined in this system, both for resorts and accommodation, can be critiqued by group members. All the members' feedback can be aggregated and recommendations that satisfy the group as a whole are ultimately generated.

Based on the traditional and advanced recommendation techniques discussed above, Sections 3 to 10 respectively will present eight application domains of recommender systems and show how these recommendation techniques are implemented and used.

3 E-government recommender systems

Electronic government (e-government) refers to the use of the Internet and other information and communication technologies to support governments in providing improved information and services to citizens and businesses. The rapid growth of e-government has caused information overload, leaving businesses and citizens unable to make effective choices from the range of information to which they are exposed. Increases in this information overload could clearly hamper the effectiveness of e-government services, and difficulties in locating the right information for the right users will increasingly impact on the loyalty of users. Recommender systems can overcome this problem and have been adopted in e-government applications [74, 75].

In this section, we will review the developments and applications of e-government recommender systems, in particular e-government Web interface personalization and adaptation and e-government service recommendation, which include government-to-citizen (G2C) and government-to-business (G2B) services.

3.1 G2C service recommendation

To support citizens in their access to personalized and adapted services supplied by public administration offices, a multi-agent system was presented by De Meo et al. [76]. The proposed system identifies and suggests the most interesting services for a user by considering both the user's profile and the profile of the device being used. To assist voters to make decisions in the e-election process, a recommender system was proposed [75], which uses fuzzy clustering methods and provides information about candidates close to voters' preferences. To provide personalized exercises to patients with low back pain problems and to offer recommendations for their prevention, a recommender system called TPLUFIB-WEB was presented in [77]. The system can be used in any place and at any time, yielding savings in travel and staffing costs. It is very user-friendly, designed for individuals with minimal skills and using fuzzy linguistic modeling to improve the representation of user preferences and facilitate user-system interactions. TPLUFIB-WEB satisfies the Web quality standards proposed by the Health On the Net Foundation (HON), Official College of Physicians of Barcelona, and Health Quality Agency of the Andalusian Regional Government, endorsing the health information provided and warranting the trust of users.

3.2 G2B service recommendation

In G2B services, many items from a business perspective are one-time items, such as events, which typically receive ratings only after they have ended. Traditional CF techniques cannot recommend these kinds of items due to the sparse rating data. To handle this problem, Guo and Lu [74] proposed a new approach which handles an attribute-considered recommendation issue by integrating the semantic similarity techniques with the traditional item-based CF. A recommender system called Smart Trade Exhibition Finder (STEF), which suggests suitable trade exhibitions to businesses, has been developed. To flexibly reflect the graded/uncertain information in the G2B domain, Cornelis et al. [78] modeled user and item similarities as fuzzy relations. They also proposed a novel hybrid CF-CB approach whose rationale is concisely summed up as "recommending future items if they are similar to past items that similar users have liked". A hybrid fuzzy logic-based recommendation framework was then developed [49] to improve the trade exhibition recommender system for e-government.

To support government to effectively recommend the proper business partners (e.g., international buyers, agents, distributors, and retailers) to individual businesses (e.g., exporters), a recommender system called BizSeeker [79] was developed. Business users can obtain a recommendation list of potential business partners from BizSeeker, as shown in Figure 1. A product semantic relevance model was proposed to calculate semantic similarity, and a hybrid semantic recommendation approach combining item-based CF similarity and item-based semantic similarity techniques was then developed. A real-world case study shows that BizSeeker helps to resolve the sparsity problem and increases recommendation accuracy. To handle linguistic terms in users' interests and the opinions of experts on product relevance, a fuzzy similarity measure and a hybrid fuzzy semantic recommendation (HFSR) approach based on BizSeeker were proposed [10]. These were implemented to solve the fuzzy problems, thereby improving the BizSeeker recommender system and elevating it to Smart BizSeeker [10]. Because business profiles usually present complicated tree structures and users' preferences are vague and fuzzy, a fuzzy preference tree-based recommender system for personalized B2B e-services was developed and applied to the business partner recommender system [80].

To improve similarity accuracy in G2B recommender systems on the BizSeeker platform, the ratio of common users who rated both items to the total number of users who rated each item individually was considered, and an enhanced item-based CF approach was presented [81] in the G2B e-government domain. In the business partner selection process, trust or reputation information is crucial and has significant influence on a business user's decision regarding whether or not to do business with other business entities. A hybrid trust-enhanced CF recommendation (TeCF) approach, which integrates the implicit trust filtering and enhanced user-based CF approaches, was proposed [22, 81] to alleviate the sparsity and cold start user problems and achieve better accuracy.

In addition to traditional CF and CB techniques, ontology, Semantic Web, agent, and fuzzy techniques are used in the above-mentioned STEF, BizSeeker and Smart BizSeeker recommender systems to form a set of hybrid recommendation approaches to improve personalized e-government service performance.

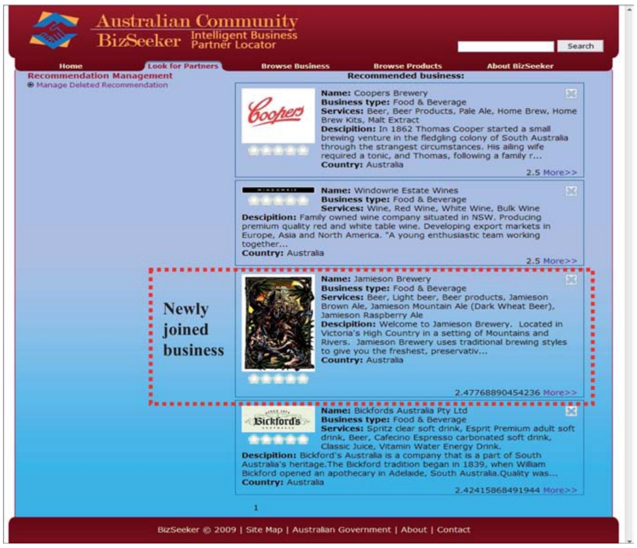

Figure 1. The recommendation list of potential business partners generated by BizSeeker [79]

4 E-business recommender systems

Many recommender systems have been developed for e-business applications. In general, some systems focus on recommendations generated to individual customers, which are business-to-consumer (B2C) systems, while others aim to provide recommendations about products and services to business users, which are business-to-business (B2B) systems. In this study, e-business recommender systems refer to recommender systems for B2B applications. E-commerce/e-shopping recommender systems refer to recommender systems for B2C applications. In this section, B2B (e-business) recommender systems are reviewed. The e-commerce/e-shopping recommender systems will be reviewed in the next section.

To help catalog administrators in B2B marketplaces maintain up-to-date product databases, an ontology-based product-recommender system was presented [82], in which keyword-based, ontology and Bayesian belief network techniques are used to generate recommendations. To help business users select trusted online auction sellers, a recommender system was designed [83] in which trading relationships are used to calculate the level of recommendations. Recommender systems were also applied in digital ecosystems where agents negotiate services on behalf of a number of small companies [84]. To build stable digital business ecosystems by means of improved collective intelligence, a model of negotiation-style dynamics from the point of view of computational ecology was introduced in [84], which inspires an ecosystem monitor and a novel negotiation-style recommender. To help private bankers provide suitable investment portfolios to their clients, a multi-investment recommender system PB-ADVISOR was presented [85]. The system used both semantic technologies and fuzzy logic to improve recommendation quality. The semantic characterization of the investments and their characteristics enable the private banker to recommend a wide spectrum of products with very diverse characteristics. The relations between investments and investors are defined by means of fuzzy rules that represent expert advisor knowledge. The results obtained have shown that the system is able to offer recommendations comparable with those from experts in the field.

Figure 2. Plan and package recommendation for a customer in the Fuzzy-based Telecom Product Recommender System [9]

Customer relationship management is very important for the telecom industry. To support telecom companies in recommending suitable products and services to their business and individual customers, a telecom recommender system has been developed [9]. Zhang et al. [9] designed and implemented a personalized recommendation approach and a software system called fuzzy-based telecom product recommender system (FTCP-RS). The FTCP-RS can generate the service plan and package recommendations for a customer and can also give recommendation explanations, as shown in Figure 2. To deal with sparsity problems and improve prediction accuracy, particularly in handling customer data uncertainty and fully using business knowledge in the recommendation process, the proposed approach integrates item-based CF (IBCF) and user-based CF (UBCF) with fuzzy set techniques and a KB method (business rules). The implemented system has undergone preliminary testing in a telecom company and has achieved excellent performance.

We found that in e-business recommender systems, the KB approaches, such as ontology and semantic techniques, are widely integrated with CF and CB recommendation methods. The main reason for this is that e-businesses have a high need for domain knowledge to assist their recommendations.

5 E-commerce/E-shopping recommender systems

In the last few years, a number of unique e-shopping recommender systems have been developed to provide guidelines to online individual customers. E-shopping is a specialized and highly popular field of e-commerce.

Rating is a common function in e-shopping systems, especially for electronic products. For example, in the iTunes[1] store, customers are able to provide feedback by allocating a value between 1 and 5 to purchased items (tracks or albums). These rating data can subsequently be used to make recommendations. Tagging is another way to connect user-item data. For example, users of the movie review site Movielens [21] are able to assign tags freely to a movie by using simple words. Correspondingly, CF [21] and social tag analysis [86] are two effective techniques in such systems when used separately [86] or collectively [44] with both ratings and tags to enhance recommendation performance.

Many of the largest commerce websites, such as Amazon and eBay, already use recommender systems to help their customers find products to purchase [17, 87]. In these B2C e-commerce websites, products can be recommended based on the top overall sellers, customer demographics, or an analysis of the past buying

[1] The music purchasing and reviewing site of Apple.com: http://www.apple.com/itunes/

behavior of the customer as a prediction for future buying behavior. Some advanced models are also proposed by academic literatures for different criteria of e-shopping environments. For example, KB analyses are usually employed in systems where it is difficult to collect user rating data. The Wasabi Personal Shopper (WPS) [88] is a domain-independent database browsing tool designed for online information access, particularly for electronic product catalogs. WPS is based on a line of academic research called the FindMe system. FindMe is built in several different languages, and uses custom-built ad-hoc databases and KB similarity retrieval. Fuzzy techniques are also employed in CB e-shopping recommender systems; for example, Cao and Li [48] developed a fuzzy-based recommender system for products made up of different components. When buying a laptop, for instance, shoppers may consider the individual performance of each component, such as the CPU, motherboard, memory, etc. In this application, the weights of a shopper's needs on each component are collected and the most satisfied candidates are then generated according to a fuzzy similarity measure model.

Mooney and Roy [89] proposed a content-based book recommender system utilizing information extraction and a machine-learning algorithm for text categorization. A naive Bayesian text classifier is used to train the data abstracted from the Web to build features of books and profiles of users and find the best matched books for a target user. In some music sharing websites such as the Last.fm system, the music social community is made up of various types of music and user relations. To better utilize the rich social information, a hypergraph model is introduced in the music recommendation approach proposed in [90] to treat the rich social media information. Certain shopping assistant systems have an interest in explaining the recommendations made to users. For example, when buying expensive goods, buyers expect to be skillfully steered through the options by well-informed sales assistants who are capable of balancing the user's various requirements. In addition, users often need to be educated about the product-space, especially if they are to understand what is available and why certain options are recommended by the sales assistant. To provide an equivalent virtual recommendation explanation such as "why product A is better than B", McCarthy et al. [91] developed a shopping assistant website called Qwikshop.com on which compound critiques were used as explanations. A set of *critique patterns* is generated by comparing each remaining case to the current recommended case; the relative feature differences make up the critique pattern. The best candidate products, for example those with the highest cost-performance ratio, will be recommended to users. Another issue is the purchase of a bundle of items or bundle promotion. In the systems developed by Garfinkel et al. [92], the authors extended the one-product-at-a-time search approach used in "shopbot" (a shopping search engine) implementations to consider purchasing plans for a bundle of items. This recommender system leverages bundle-based pricing and promotional deals frequently offered by online merchants to extract substantial savings.

With the increasing use of mobile phones and the advances in wireless networks, recommender systems are not only available for Web users but are also being provided to mobile users as mobile-based recommender systems. Lawrence et al. [93] designed a mobile personalized recommender system to suggest new products to supermarket shoppers, who use Personal Digital Assistants (PDAs) to compose and transmit their orders to the store where they are assembled for subsequent pickup. The association mining method is used to determine relationships among product classes for use in characterizing the appeal of individual products. Clustering is used to identify groups of shoppers with similar spending histories. Cluster-specific lists of popular products are then used as input to a matching process of customers and products to generate recommendations.

In summary, e-shopping recommender systems (Web-based and mobile-based) are usually implemented in online purchasing for both digital products (music, movies, etc.) and physical goods (books, bags, etc.). From the application perspective, researchers have developed a number of successful e-shopping systems in which to employ their novel algorithms. These systems provide guidelines for developers about how to practically implement recommender systems for e-shopping.

6 E-library recommender systems

Digital libraries are collections of digital objects, along with the associated services delivered to user communities [94]. Recommender systems can be used in digital library applications to help users locate and select information and knowledge sources [95]. In this section, e-library recommender systems are reviewed.

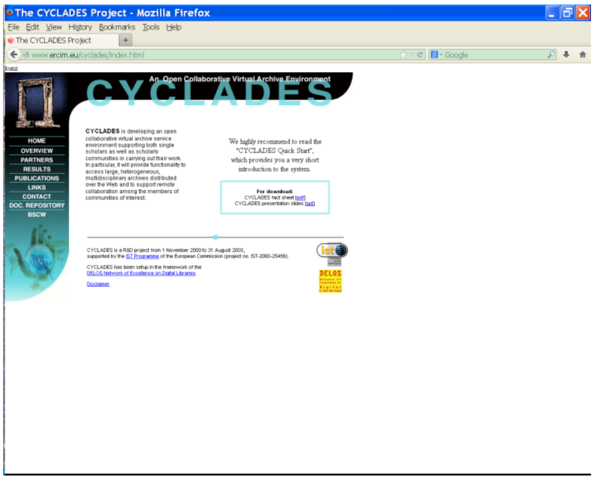

Figure 3. The home page of CYCLADES

Fab, part of the Stanford University Digital Library Project, was reported in [96]. It is a hybrid recommender system which combines both the CB and CF recommendation techniques. To provide better personalized e-library services, a system called CYCLADES (http://www.ercim.org/cyclades), shown in Figure 3, was subsequently presented [97]. CYCLADES provides an integrated environment for individual users and group users (communities) in a highly personalized and flexible way. The recommendation algorithms rely on both personalized information organization and users' opinions, and use CB and CF methods separately and in combination.

Porcel et al. researched and developed a recommender system to recommend research resources in University Digital Libraries (UDL) [95, 98]. A fuzzy linguistic recommender system was proposed in which multi-granular Fuzzy Linguistic Modeling (FLM) was used to represent and handle flexible information by means of linguistic labels, and a hybrid recommender system that combines both CB and CF approaches was presented. To reduce the user input effort, users are allowed to nominate their preferences by means of incomplete fuzzy linguistic preference relation. Based on the above researches, Serrano-Guerrero et al. [99] presented a recommender system which can incorporate Google Wave technology in UDL.

In the e-library recommender systems discussed above, the hybrid recommendation approaches which combine CB, CF and/or KB techniques are widely used. One reason to use hybrid approaches is that they take advantage of the merits of several different recommendation techniques. Fuzzy techniques, in particular multi-granular fuzzy linguistic modeling, are used to represent and handle the flexible information of linguistic labels.

7 E-learning recommender systems

E-learning recommender systems have become increasingly popular in educational institutions since the early 2000s based on the development of traditional e-learning systems. This type of recommender system usually aims to assist learners to choose the courses, subjects and learning materials that interest them, as well as their learning activities (such as in-class lecture or online study group discussion). In more than ten years' accumulated study on this topic, many practicable e-learning recommender systems have been developed.

Zaiane [100] proposed an approach to build a software agent that uses data mining techniques such as association rule mining to construct a model that represents online user behaviors, and used this model to suggest activities or shortcuts. The suggestions generated assist learners to better navigate online material by finding relevant resources more quickly using the recommended shortcuts. A personalized e-learning material recommender system (PLRS) was proposed in the work of Lu [101]. Once a learning material database or a learning activity database is created and a learner's registration information is obtained by the system, the PLRS uses a computational analysis model to identify an individual's learning requirement and then uses matching rules to generate a recommendation of learning materials (or activities) for the learner. Web usage mining is the process of applying data mining techniques to the discovery of behavior patterns based on Web click-stream data, which provides information to help understand users' preferences. A recommender system that utilizes Web usage mining to recommend the links in an adaptive Web-based educational system was proposed in [102]. A Web mining tool and a recommendation engine were developed and applied into the Adaptive Hypermedia for All (AHA!) system to help the instructor to carry out the whole Web mining process. In the personalized courseware recommender system (PCRS) continuously developed in [103] and [104], a fuzzy item response theory (FIRT) is proposed to initially collect a learner's preferences, following which the learner provides a fuzzy response as a percentage of their understanding of the learned courseware. The system framework of [103] contains both online and off-line modules. The online modules provide the evaluations of a learner's preference and the matching process between learners and courseware. The off-line module provides a courseware management agent to assess the level of difficulty of each course, in support of the matching process. To recommend learning goals and generate learning experiences for learners, a recommendation methodology was defined and a recommender system prototype component developed for integration into a commercial adaptive e-learning system called IWT [105]. The recommendation methodology applies a hybrid recommendation approach which consists of three steps: concept mapping, concept utility estimation and upper level learning goals (ULLG) utility estimation. Once the utility of each ULLG is estimated for a learner, the ULLGs with the greater utility can be suggested to the learner.

In another e-learning recommender system, CourseAgent, developed by Farzan and Brusilovsky [106], students are able to provide feedback in implicit and explicit ways. They can directly evaluate courses in respect of their relevance to each career goal as well as the difficulty level of the course. They can also provide implicit feedback when they plan or register for a course. The basic and evident benefit of the system to students is that it offers a course management system that retains the information about courses they have taken and facilitates communication with their advisors. This work is a good attempt at providing social navigation support and community-based recommendations which generate benefit to users and therefore offer encouragement to use the system. In addition to implicitly mining from Web usage or explicitly obtaining recommendations through a response/feedback system, relevant pedagogical rules should also be considered. Pedagogical rules describe pedagogy-oriented relations between the characteristics of learners and the characteristics of learning activities [107]. For example, a recommender system of pedagogical patterns

(RSPP) was developed in [108] to help lecturers choose a proper pedagogical pattern and define the best teaching strategies. RSPP defines an ontology to represent the pedagogical patterns and their interaction with the fundamentals of the educational process, and applies a unified hybrid model which combines content and CF to make recommendations. To extend Web-based educational systems with personalized support, a user-centered design approach was proposed and applied to the Willow system [109]. This study indicates that building personalized learning e-environments is a process that must consider learners' needs throughout the e-learning life cycle. It also reported that the e-learning life cycle can be used to design and evaluate personalization support through recommendations in Web-based educational systems.

The corresponding ontologies of learners and learning objectives are discussed in the literature. Biletskiy et al. [110] described a technical solution for a personalized search of learning objects on the Web which proposes a comparison of learner (user) profiles and learning object descriptions. This comparison is based not only on the values of the attributes of learner profiles and the attributes of the learning object descriptions, but also on the importance of these attributes for the learner. In the framework, a comparator is proposed to evaluate the "matching score" between learners and learning objectives, based on comparison rules.

From the above reviews, it is clear that KB pedagogical rules play a more important part in making recommendations in e-learning recommender systems than they do in other recommender systems, because such recommender systems usually lack sufficient historical data sets for CF or CB algorithms. The architecture of an e-learning recommender system usually consists of three parts: 1) using Web analysis techniques to collect learners' profiles and identify their personalized demands; 2) collecting the metadata of learning objectives to identify the features; 3) acquiring related pedagogical knowledge to evaluate the matching degree between learners and learning objectives. It also should be mentioned that some advanced techniques are also integrated in the matching process to improve system performance.

8 E-tourism recommender systems

Internet and mobile devices provide tourists with great opportunities to access tourism information, but the dramatic increase in the number of available tourism choices make it difficult for tourists to choose which option they prefer. E-tourism recommender systems are designed to provide suggestions for tourists. Some systems focus on attractions and destinations, while others offer tour plans that include transportation, restaurants and accommodation.

There are several restaurant recommender systems. Burke et al. [111], for example, proposed a recommender system called Entrée to recommend restaurants based on KB approaches. The knowledge was collected from users and retrieved by Entrée to find similar choices by refining such search criteria as price and taste. Burke [14] improved Entrée by incorporating CF into KB, which meant that apart from restaurant features, the assessments of users also became criteria.

As we mentioned before, mobile devices provide opportunities for the development of mobile-based recommender systems. Hung-Wen and Von-Wun [112] designed a system to suggest restaurants for tourists in Taipei. This system is a CB recommender system which allows users to obtain real time suggestions from a mobile application. CATIS [113] is a context-aware recommender system which recommends tourist accommodation, restaurants and attractions. The context information (e.g., location and wireless device features) is dynamically collected by a context manager. A collection of Web services provided by an application server is used to gather user context information. The recommendations are generated by combining the user query and the user context information from the application server.

Another restaurant recommender system, REJA (REstaurants of JAén) hybridizes CF and KB approaches [114]. The recommendations can be provided by the CF approach when the system is able to construct a user profile according to the user's ratings. When the system has insufficient information about a user, a case-based reasoning approach is executed.

A personalized sightseeing planning system (PSiS), which is used to aid tourists to find a personalized tour plan in the city of Oporto, Portugal, was developed in [115]. To avoid the shortcomings of current recommender systems, such as scalability, sparsity, first-rater and gray sheep problems, a hybrid recommendation approach was proposed. The proposed hybrid recommendation approach employed CF and CB approaches, combined a clustering technique and an associative classification algorithm, and also used fuzzy logic to enhance the quality of recommendations. SigTur/E-Destination [116] was designed to provide personalized recommendations of tourism activities in the region of Tarragona. To make proper recommendations, the SigTur/E-Destination integrated several types of information and recommendation techniques. The information used in the recommender includes demographic data, details that define the context of the travel, geographical aspects, information provided explicitly by the user and implicit feedback deduced from the interaction of the user with the system. The SigTur/E-Destination employs many recommendation techniques, such as the use of stereotypes (standard tourist segments), CB and CF techniques, and artificial intelligence tools including automatic clustering algorithms, ontology management, and the definition of new similarity measures between users, based on complex aggregation operators.

SMARTMUSEUM, a mobile-based recommender system, presents users with recommendations for sites and objects on those sites on their mobile phones [117]. In this system, an ontology-based personalization, annotation, and information filtering framework was developed. The contextual data, whether input by users or captured by the built-in sensors of mobile devices, are mapped to the concepts defined in the ontologies. The filtering framework introduced ontology-based query expansion for triples, feature balancing, and result clustering, which led to significant improvements in the accuracy of information filtering. iTravel, another mobile-based recommender system, was developed to provide tourists with on-tour attraction recommendation [118]. In this system, the techniques of CF and mobile peer-to-peer communication were combined. To utilize the information of other tourists with similar interests in mobile tourism, three data exchange methods for users to exchange their ratings of attractions they had visited were proposed.

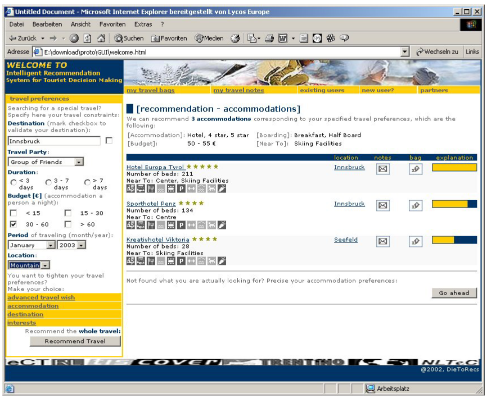

Figure 4. DIETORECS recommender system webpage [119]

Moleskiing [120] is a website for assisting community users to plan their skiing activities. This recommender system allows users to share their opinions and experiences of particular sites as well as the trust degrees for specific users. People who are going skiing can exploit the snow condition information to personalize a safe route. DIETORECS [119] is a case-based reasoning (CBR) recommender system which creates a complete plan for tourists (see Figure 4). Users can utilize the system in different ways according to their experience. The experienced user can make detailed preferences for attractions, while the less-experienced user can simply make a list of attractions of interest. An on-board recommender system for drivers called MASTROCARONTE [121] utilizes KB approaches to recommend attractions, restaurants, and hotels. It utilizes context information to suggest appropriate items to drivers such as restaurants at meal times or nearby fuel stations when fuel is exhausted.

The SPETA system [122] uses the knowledge of a user's current location, preferences, and the history of past locations to recommend the services that tourists expect from a human tour guide. It combines social networks, Semantic Web, and context-awareness in pervasive systems to improve tourists' experiences. It offers a personalized guide, and solves the problem of tourism service disintegration in respect of searching, finding and presenting personalized services by means of semantic, geo-location, and social technologies. Traveller [123] is proposed to provide package holidays and tours. It builds an agent which combines CF with CB and demographic recommendation approaches.

In summary, various recommendation techniques are applied in e-tourism recommender systems according to the degree of complexity and requirements of their recommended items. For recommending relatively simple items, such as restaurants, CB and CF techniques are usually applied. For recommending more complex items, such as travel routes and time schedules, KB and hybrid recommendation techniques with domain knowledge are utilized. For recommending items with real time requirements, such as fuel stations, context awareness-based techniques are used.

9 E-resource service recommender systems

The e-resources mentioned here refer to content such as videos, music and documents which is uploaded by users. Some recommender system users share sources to the Internet so that other users can access the resources that interest them. This section focuses on several typical applications of recommender systems in resource services: Tag, TV program, webpage, document, video and movie recommendation.

9.1 Tag recommendation

Tags are arbitrary words specified by users to label and manage the resources that are uploaded to the Internet. Users want tags to be personalized and convenient to enable the easy sharing of resources, but it is often difficult for users to select appropriate tags from the wide range of possibilities. Tag recommender systems thus become increasingly important for making tag selection easy and personalized.

Folksonomies, which contain tag recommender systems, are Web-based systems that allow users to upload their resources (e.g., documents, pictures), and to label them with tags. Folksonomies can be seen as three-part systems comprised of resources, users and tags. Zheng and Li [124] implemented a folksonomy recommender system based on CF. They exploited the tag and time effects in the recommendation procedure. Instead of utilizing the rating matrix in traditional CF, they built matrixes based on tag and time relations. Three strategies, tag-weight, time-weight and mixed, are used to calculate the similarities based on corresponding matrixes. The recommendations are predicted by neighbors who are identified based on new similarities.

Another tag recommendation approach, FolkRank, was proposed in [125, 126], in which the tags are recommended by calculating the distance from the uploaded resource. Gemmell et al. [127] suggested that CF, especially item-based CF, could be incorporated into the traditional graph-based approach to augment the performance in FolkRank. The item-based CF identifies the relevant resources by tags that are common to the user. The final recommendations are predicted by the linear combination of graph-based and CF approaches.

9.2 TV program recommendation

TV programs can be seen as a special type of resource released by broadcasters. A large increase in the number of TV channels and programs has been seen in recent years due to the growth of interactive and two-way TV. Even with an electronic program guide, it is difficult for viewers to find interesting programs from the hundreds or thousands of options. A program recommender system (PRS) is required to help viewers to choose programs that interest them.

Content information for TV programs can be described by features (e.g., genre, actor), so the CB method is commonly used; where the TV mode allows the user to give feedback (e.g., ratings), the CF method is well applied. In PTV (http://www.ptv.ie), proposed by Smyth and Cotter [128], viewers rate programs through a Web system to specify their preferences. After the system has collected explicit data from viewers, both CF and CB methods are used to find similar programs according to the ratings given by viewers and the program information.

With the development of smart TV sets, users are allowed to give ratings on TV, which has resulted in TV-based recommender systems. TiVo [129] allows viewers to rate programs using the remote control, and CF is utilized to suggest suitable programs (see Figure 5). The implicit feedback, such as whether the program is being recorded, is taken into account in addition to the explicit ratings from viewers. Requiring users to respond to programs is tedious and raises privacy issues, so some systems try to collect the required data in the background. User preferences are built using program attributes such as program title, genre, subgenre, channel, and actors in [130]. TV programs are recommended by comparing the features of the past viewing set with current programs. Hyeong-Joon and Kwang-Seok [131] proposed a novel similarity method that applies raw moment-based similarity (RMS) which is then used in memory-based CF approaches to address such shortcomings as cold start and high calculating cost. The application queveo.tv, developed by Barragáns-Martínez et al. [132], combines the CB approach and item-based CF approach to address the problems of gray sheep, cold start and first rating. The dimensionality reduction technique, singular value decomposition, is incorporated to solve sparsity and scalability problems.

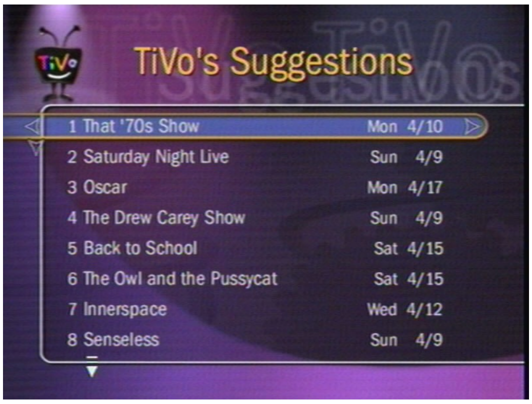

Figure 5. TiVo Program Recommender System recommendation list [129]

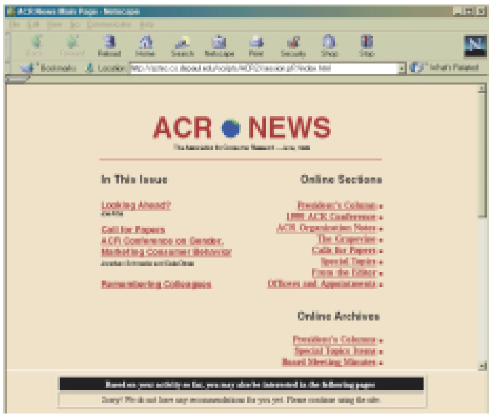

Figure 6. The home page of ACR News [133]

Other than memory-based CF and CB approaches, a number of model-based approaches have also been utilized in PRS. Zimmerman et al. [134] made suggestions based on the implicit and explicit feedback from viewers to infer the probability of whether a user watches a program. A Bayesian classifier and a decision tree model are trained to learn the implicit data and view history, and a neural network is trained to learn the explicit data and viewer specification. Fernandez et al. [135] implemented the AVATAR system, which uses semantic analysis to measure the similarity between two programs.

9.3 Webpage, news and document recommendation

Suggesting webpages, documents and news is a traditional area for recommender systems because such resources grow rapidly. In most instances, textual content such as news, emails, documents and webpages is described as a list of keywords, which can be extracted from historic data, URLs and search engines, and many recommender systems are designed on the basis of analyzing keywords. Probabilistic models such as the information retrieval technique are common in this area. Contextual resources are transformed to a vector, with each element representing a keyword which takes frequency and location (title or plain text) into account. The recommendations are generated by retrieving resources that are similar to the user patterns. For example, AMALTHAEA [136, 137] draws keywords from URLs by examining the hotlist and browsing history, and investigates the interest shown by users by information retrieval (IR). CB approaches are adopted in ifWeb to measure the similarity between pages [138]. CF is feasible if systems can collect information about whether users evaluate the content by ratings. For instance, News Dude [30], a news recommender system, uses CF to model users' short term interests. Other examples of systems in which CF is used are the joke recommender system Eigentaste [139] and the Usenet news recommender system GroupLens [21, 140]. In addition to News Dude [30], which builds long-term preferences through Bayesian methods, other model-based systems have also been proposed, such as Foxtrot [141], which uses k-nearest classification. Graph-based clustering was adopted in WinPUM [142], in which the authors transformed websites into graphs and classified user navigation patterns according to users' session information. Recently, Nguyen et al. [143] suggested that by integrating ontology and semantic knowledge, which are used to analyze session data, the system could navigate more accurately. In Eigentaste [139], principal component analysis is adopted to deduce the dimension of a keywords matrix to accelerate the process of user clustering and the computation of recommendations.

Apart from the keywords taken from the textual content, implicit and explicit feedback from users is also taken into account. Lifestyle Finder [144] uses demographic information to model the user and provide webpage recommendations. ACR News Vectors [133] are built based on implicit feedback and viewing frequency for webpages (see Figure 6). The clustering model is then trained and pages are recommended by a CB approach on related clusters. In ArgueNet [145], another webpage recommender system, users are allowed to address such criteria as the trustworthiness of websites. The user preferences are modeled by keywords along with these criteria to generate personalized recommendations.

9.4 Movie, video and music recommendation

With the extensive usage of mobile devices in recent years, a particularly rapid growth in movie, video and music resources has taken place. However, users experience frustration when searching for content that interests them on mobile devices. To solve the problem, many movie recommender systems, such as PocketLens [146] and CinemaScreen [147], and music recommender systems such as Flycasting [148], Smart Radio [149], RACOFI [150] and Foafing the Music [151], have been developed. Because most of these systems allow users to rate resources, CF recommendation approaches are commonly used in these recommender systems. In some systems, such as Flycasting [148], users cannot rate music directly, so this system first translates historical listening information into ratings and then carries out CF. To address the cold start and sparsity problems of CF approaches, CB approaches are incorporated in some systems. For example, Melville et al. [152] utilized CB to overcome the sparsity and first-rate problem. CinemaScreen [147] also used a CB method to solve cold start problems in movie recommendation. One feature of movie and music recommender systems is that it is not easy to obtain the content and navigation history from multimedia resources. These resources contain such features as artist and genre, and how to extract the underlying correlations is an important issue in this area. Model-based approaches like semantic analysis and social network are also integrated into CF. RACOFI [150] utilizes Semantic Web techniques. Foafing the Music [151] maintains friend of friend profiles which work in a similar way to social networks. CoFoSIM [153], a mobile music recommender system, utilizes multi-criteria decision-making (MCDM) techniques to analyze the implicit feedback and partial listening records, and aggregates them into a composed preference. An interesting aspect of music recommender systems is that some systems use implicit feedback to augment or replace the explicit ratings from users. For example, both CoFoSIM [153] and Smart Radio [149] use the listening history to infer their user ratings.

In general, these resource service recommender systems aim to organize and manage this type of Web service content and save users from performing tedious searches. In the tag domain, the CF method is the dominant recommendation technique. For TV programs, intelligent techniques such as Bayesian classifier, decision tree and semantic analysis are integrated with CF and CB methods to implement recommender systems. Recommending contextual content, such as webpages and documents, is a traditional application area of CB and CF methods, as well as memory-based approaches, and model-based approaches, such as Bayesian and clustering techniques, are all utilized. Social and context-aware techniques play an increasingly important role alongside traditional CB and CF in movie and music recommendation.

10 E-group activity recommender systems

There are some scenarios (e.g., recommending a TV program to a group of people) in which users are unable to specify their preference explicitly, and some scenarios (e.g., taking a tour with others) in which users need to negotiate online to engage in an activity together. In these cases, people need online decision support for a whole group. Traditional recommender systems only make suggestions for individual users, thus group recommender systems (GRS) are proposed to combine and balance the individual expectations of group members to produce satisfying recommendations to the group. There are two main types of GRS: one called an off-line GRS for a group which has already been formed (a family, for example), and one called an on-line GRS for a group which needs to be formed by the system. GRS have been applied in practice for both types. We summarize the four main domains below.

10.1 Book, document and webpage recommendations for groups

Many GRS are designed to recommend books, documents and webpages. Probabilistic-based models such as information retrieval, Bayes and user-item matrix are utilized to describe items and present the relationship between those items and users. I-SPY is a search engine that recommends resources to communities of likeminded users [154-156]. The system maintains a hit matrix, connecting the users and queries for a community, and updates the matrix when a user visits the search results. The relative resource is re-ranked after the matrix is updated, and other users in the community can obtain more accurate results. Besides utility, other requirements are taken into account in GRS, such as satisfaction and fairness.

GRec_OC is a book recommender system developed by Kim et al. [157] to validate their approach for an online community. Their intention is to satisfy the small number of group members who are likely to be ignored although the majority of the community is satisfied. They adopt two levels of filtering mechanism, CB and CF-based methods, to generate candidate books by CF according to the group preference, and eliminate candidate books if any member's compatibility score is below the threshold.

To augment browsing activities, Sharon et al. [158] proposed a mediator, Context Aware Proxy-based System (CAPS), to collect the frequency and dwell time for pages, which works as a proxy for browsers without requiring the user to input data actively. The repositories for a group of collaborative members and ranks for pages are built to augment other members' browsing and searching activity.

10.2 Movie and music recommendations for groups

Some music recommender systems automatically broadcast music to users without user selection; these are referred to as radio-based recommender systems. For example, MusicFX [159] is a GRS that recommends music to all the people in a gym. Members' preferences are stored in the system, and the recommended music is generated according to personal preferences and played for members without further selection. Flytrap [160] is another GRS that selects music to be played in a public room. Instead of collecting personal preferences by asking, Flytrap automatically collects meta information about the music that the user is listening to. Genres and artists are used to build a network with edges between network nodes representing the similarity between them. The playlist is ultimately determined by a voting mechanism, with some constraints predefined by the system. Like a threshold on rating to measure a particular kind of music, the similarity combined related threshold can also be used to measure preference. In [161], adaptive radio is proposed to broadcast songs to people who share the radio. The system adopts a simple mechanism whereby rejected songs, or other songs which are similar to the rejected ones, will not be played, whereas recommendations will be broadcasted and played automatically.

PolyLens [69], which supports group creation and management, is extended from MovieLens and is designed for movie recommendation for a relative small group. It considers the nature of the group, the group's formation and evolution, privacy, group recommendation generation and interfaces. PolyLens merges the recommendations generated for individual users by nearest neighbor methods and sorts the merged list according to the lowest ratings ascribed to the movie; it can therefore provide more information to both individuals and the group.

Features of users and items can be collected to measure the relevancy between multimedia resources and users and therefore generate highly accurate group recommendations. Knowledge from domains has also been incorporated into recommendation techniques. Recio-Garcia et al. [162] took the member personality composition into account. A Thomas-Kilmann Conflict Mode Instrument (TKI) test, which is common in the human resource domain, is implemented for every member, and two measures are generated to depict member behavior patterns, assertiveness and cooperativeness. Recio-Garcia et al. [162] then proposed the Conflict Mode Weight (CWM) method which incorporates CF to generate recommendations and improves the recommendation quality tested by MovieLens.

10.3 Tourism recommendations for groups

Figure 7. CATS tourism system critiquing interface [73]

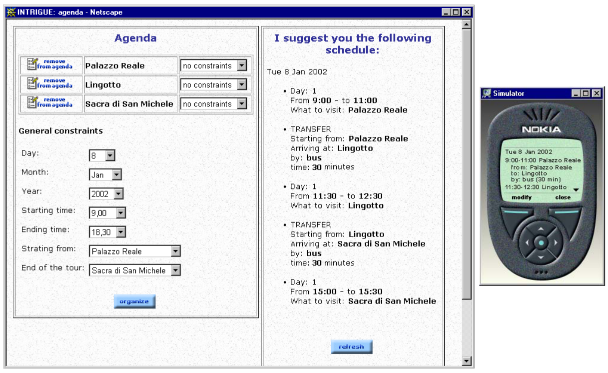

Figure 8. INTRIGUE system preference specification interface [163]

Attractions, accommodation and restaurants are often recommended to groups in tourism GRS, and their features are used to form group recommendation lists. Pocket Restaurant Finder [164] is a GRS that locates a restaurant for a group of people. Every member presents their opinions, stipulating such conditions as distance, price and so on. This GRS builds a group preference model and evaluates each restaurant according to the model. The final recommendations are produced as a list. CB approaches are mainly used to produce personal preferences. The Collaborative Advisory Travel System (CATS) was proposed in [73, 165] to recommend a plan for ski holidays for a group of friends (see Figure 7). Users present their explicit critiques for the features of the plan and negotiate to reach agreement on those critiques, called the group user model. The system produces recommendations according to this model. INTRIGUE [163, 166] is a tourism GRS that is also based on aggregating recommendation approaches (see Figure 8). The group is first divided into several subgroups according to the demographic information (e.g., number of children). Recommendations are generated for each subgroup and the final result is built by taking into consideration the influence of subgroups (e.g., people with disabilities). Personalized Electronic Tourist Guides (PETs) [167] provides a solution for personalized route generation based on the profile and constraints of a group of tourists. The solution is integrated by three aspects: demographic information, route information and specified preference. With each aspect, a group preference model is constructed and recommendations are added to a candidate list. e-Tourism [168] generates recommendations about personalized tourist tours in the city of Valencia (Spain) for a single person or a group of tourists. In the e-Tourism system, group preferences are elicited from individual preferences through the application of intersection and aggregation mechanisms. Instead of making recommendations that directly match the group preferences, e-Tourism also applies a hybrid recommendation technique by combining demographic, content-based recommendation and likes-based filtering, which ensures that e-Tourism is always able to offer a recommendation, even when the user profile contains very little information. In [169], a multi-agent recommender system for tourism was developed based on the cooperation of two types of agent: user agent and recommender agent. The user agent stores the user preference information and the recommender agent stores the travel information locally. The recommendations are produced by the exchange of information between these two types of agent. For users who want to plan a vacation together but find it difficult to negotiate face to face, the tourism GRS also takes negotiation support into consideration. Jameson et al. [170] proposed a system called Travel Decision Forum that helps groups to plan a vacation using an asynchronous communication mechanism (see Figure 9). Users in a group can view and even copy other members' preferences. After the users have reached agreement, the system aggregates individual preferences with the median strategy. McCarthy et al. [73] proposed a CB simultaneous collaborative group critiquing recommender system to produce ski holiday suggestions for groups of up to four members. The features predefined by the system for both resorts and accommodation are critiqued by members. All the feedback is aggregated and the recommendations most likely to satisfy the group as a whole are generated.

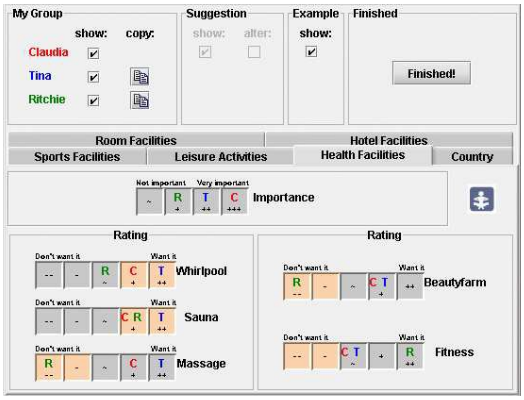

Figure 9. TDF preference specification interface [72]

10.4 TV program recommendation for groups

As mentioned in Section 9.2, TV program recommendation (TPR) has been developed and is important not only for individual personalization but also for group adaptation, such as when family members watch programs together. A challenge in making TPR different from other Web-based group recommender systems is that it is difficult to identify the members in a group because the group could be dynamic, with members able to join and leave the group at any time. In the Family Interactive TV System (FIT) reported in [171], viewers are modeled according to their stereotypes and the probability of preferred watching time for each type. The programs are recommended according to the combined probability. Another system, TV4M [172] identifies members by providing a login function. The preferences are aggregated by minimizing the feature distance. Model-based techniques are also utilized in TPR. Vildjiounaite et al. [173] built a model for a family by supporting vector machine and made suggestions using a KB approach.

Group recommender systems can be seen as utilizing individual recommender techniques to generate individual preferences or suggestions and then using aggregating methods to combine them. From this point of view, any individual recommender technique can be adopted in GRS. The special methods for GRS that differ from individual recommender systems are the aggregating methods. Another interesting aspect is modeling how group members communicate. For contextual content, music and movie recommendation, asynchronous communication is widely adopted. For TV recommendation, off-line negotiation is appropriate. For tourism recommendation, synchronous communication is adopted when group members want to guarantee tour quality.

11 Comprehensive analysis, findings and emerging research topics

Recommender systems and their applications reviewed above are summarized in this section. For each application domain, the number of reviewed recommender systems and the recommendation techniques used in the systems are summarized and presented in Table 1. From the summary of recommender systems, the following important findings can be extracted:

1) the classic recommendation approaches, such as CF, CB and KB, still play a dominant role in almost

all kinds of application, but hybrid recommender systems are more popular than single recommendation technique-based systems for avoiding the drawbacks of individual recommendation approaches;

2) of the eight main recommender system application domains, e-resource recommender systems have been the most-reported, and systems for individual users constitute the majority;

3) compared to other domains, e-learning recommender systems have highly applied knowledge-based methods, while e-resource recommender systems use more CF methods;

4) some new recommendation techniques, such as the social network-based recommender system and context awareness-based recommender system, have played an increasingly important role in recent application developments;

5) some computational intelligence techniques, such as fuzzy logic, have been applied in all kinds of recommender systems application domains to handle various uncertainties. This study reports 27 successful recommender systems that use various computational intelligence techniques;

6) some new application platforms (not traditional Web-based platforms) of recommender systems, such as mobile, TV and radio platforms, have emerged only recently. This paper lists the 10 newest mobile-based recommender systems, 9 TV-based recommender systems and 4 radio-based recommender systems.

The details of each recommender system reviewed, including its application domain, the applied recommendation techniques, application platforms, user types and periods of use, are listed in Table 2 in the Appendix.

Table 1. Summary of recommendation techniques in each application domain

Techniques / Domains	CB	CF	KB	Hybrid	Computational Intelligence	Social Network	Context Aware	Group Aggregation	No. of listed references
E-government	1	5	1	5	4				**9**
E-business		1	3	3	4	1			**5**
E-commerce/E-shopping	3	1	4	1	4	2			**8**
E-library	2	2		3	1				**6**
E-learning	2		11		2				**10**
E-tourism	5	9	9	9	3	2	11		**18**
E-resource	9	16	6	15	8	1	1		**27**
E-group activity	9	5	2	5	1			2	**21**
Total	**31**	**39**	**36**	**41**	**27**	**6**	**12**	**2**	**104**

Even though recommender system applications have obtained great development, there are still some issues requiring further research with the emerging of new e-services applications.

1) With the increasing usage of Internet-accessing smart phones, it is now possible to offer personalized and context-sensitive recommendations to mobile users, and more mobile recommender systems will be required. However, mobile data is usually more complex, which is heterogeneous, noisy, requires spatial and temporal auto-correlation, and has validation and generality problems [174]. Further research in mobile-based context-sensitive recommendations is a significant topic.

2) Later than e-commerce the further development of e-government recently promotes the applications of e-government recommender systems. E-government usually provides non-profit public welfare services, which are quite different from e-commerce domains: users usually select the e-government services based on the trust to the government; some services are related to the security of individuals and society. These factors

have not and should be considered in the future research in e-government recommender systems.

3) In e-tourism or e-shopping application domains, users prefer real time, locating and fine granularity recommendations. For example, a user in a shopping center wants to get real time and fine granularity recommendations of shops and products based on the location and time. To handle these requirements, real time context awareness-based recommendation methods need to be further investigated.

4) In e-shopping or e-learning application domains, the distribution of data, such as the users' behavior towards, their interests/preferences and the functionality of some items, keeps changing. Using the outdated data to predict users' current preferences will result in poor performance. Concept drift techniques [175] should be introduced into recommender systems to model users' preference drift and improve the recommendation performance in a fast changing environment [176]. It will be an emerging research topic.

5) Even though many research efforts have been made to deal with the data sparsity problems in recommender systems, this problem is still not solved well in many application domains. Transfer learning techniques, which can combine the relevant data from other domains into the target domain, provide a good opportunity to handle this problem [177]. Therefore, Transfer learning-based recommender systems will be another significant direction.

6) The recommendation methods adopted in a recommender system are limited by the information sources of the system. In the big data era, numerous dimensions of data can be obtained, which is helpful to model users' preferences more accurately and comprehensively. More recommender system applications are expected to be developed by effectively and efficiently utilizing the big data. For example, the development of smart wearable devices can extract more information of people, which can be used in the health and medical application domain, and result in health recommender systems.

We hope this paper can provide researchers and practical professionals with the state-of-the-art knowledge on recommender system application developments and provide guidelines about how to develop and apply recommender systems in different domains to support users in various decision activities. Two important features of this paper clearly distinguish it from other survey papers in the recommender systems area: 1) it targets and focuses the real-world application development of recommender systems; 2) it systematically examines the reported recommender systems (online software) through four dimensions: recommendation methods (such as CF), recommender systems software (such as BizSeeker), real-world application domains (such as e-business) and application platforms (such as mobile-based and TV-based platforms).

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Appendix

Table 2. Summary of recommender systems developed, the techniques applied and user type

System name	Application domain	Technique	Application platform	User type	Period	Reference
A multi-agent e-government system	e-government	KB	Web-based	Individual	2005	[76]
eElections RS	e-government	Fuzzy clustering	Web-based	Individual	2010	[75]
TPLUFIB-WEB	e-government	Fuzzy linguistic modeling,	Web-based	Individual	2014	[77]

		Hybrid, CB, CF				
Smart trade exhibition finder	e-government	CF, Hybrid	Web-based	Business	2007	[74]
A trade exhibition recommender system for e-government	e-government	CF, Hybrid, Fuzzy logic	Web-based	Business	2007	[49, 78]
BizSeeker	e-government	CF, Hybrid	Web-based	Business	2010	[79]
Smart BizSeeker	e-government	CF, Hybrid, Fuzzy sets	Web-based	Business	2013	[10, 80]
An ontology-based product RS	e-business	KB, Bayesian belief network	Web-based	Business	2006	[82]
Auction seller recommender system	e-business	Social network analysis	Web-based	Business	2008	[83]
A negotiation-style recommender	e-business	CI, a simulated-annealing inspired algorithm, greedy algorithm	Web-based	Business	2011	[84]
PB-ADVISOR	e-business	Fuzzy logic, KB	Web-based	Business	2012	[85]
Telecom recommender system	e-business	CF, KB, Hybrid, Fuzzy sets	Web-based	Business	2013	[9]
MusicBox	e-commerce	Social tag, CF, Hybrid	Web-based	Individual	2010	[86]
Wasabi personal shopper	e-commerce	CB, KB	Web-based	Individual	1999	[88]
Consumer electronic products RS	e-commerce	KB, CI, Fuzzy techniques	Web-based	Individual	2007	[48]
A book RS	e-commerce	CB	Web-based	Individual	2000	[89]
MRH	e-commerce	Social network, CI	Web-based	Individual	2011	[90]
A conversational RS	e-commerce	KB	Web-based	Individual	2004	[91]
GRAB	e-commerce	KB, CI	Web-based	Individual	2006	[92]
A supermarket product RS	e-commerce	CB, CI	Mobile-based	Individual	2001	[93]
Fab	e-library	CB, CF, Hybrid	Web-based	Individual	1997	[96]
CYCLADES	e-library	CB, CF, Hybrid	Web-based	Individual, Group	2005	[97]
University digital library Recommender system	e-library	Hybrid, Fuzzy linguistic modeling	Web-based	Individual	2009-2011	[50, 95, 98, 99]
An e-learning recommender agent	e-learning	KB, Rule mining	Web-based	Individual	2002	[100]
PLRS	e-learning	CB, KB	Web-based	Individual	2004	[101]
AHA!	e-learning	Web usage mining	Web-based	Individual	2009	[102]
FIRT	e-learning	KB, CI, Fuzzy item response theory	Web-based	Individual	2004	[103]
FIRT	e-learning	KB, CI, Fuzzy item response theory	Web-based	Individual	2008	[104]
IWT	e-learning	KB	Web-based	Individual	2014	[105]
CourseAgent	e-learning	KB	Web-based	Individual	2006	[106]
RSPP	e-learning	Ontology	Web-based	Individual	2013	[108]
Willow system	e-learning	KB	Web-based	Individual	2014	[109]
PSDLO	e-learning	KB, CB	Web-based	Individual	2009	[110]
Entrée	e-tourism	KB	Web-based	Individual	1996	[111]
EntreeC	e-tourism	KB, CF	Web-based	Individual	2002	[14]
Restaurant directory services agent	e-tourism	Context-aware	Mobile-based	Individual	2004	[112]
CATIS	e-tourism	Context-aware	Mobile-based	Individual	2003	[113]
REJA	e-tourism	CF, KB	Web-based	Individual	2009	[114]
PSiS	e-tourism	CF CB clustering associative	Web-based	Individual	2013	[115]
SigTur/E-Destination	e-tourism	CF CB demographic context	Web-based	Individual	2013	[116]

SMARTMUSEUM	e-tourism	Ontology context information filtering	Mobile-based	Individual	2013	[117]
iTravel	e-tourism	CF context	Mobile-based	Individual	2013	[118]
DIETORECS	e-tourism	KB	Web-based	Individual	2003	[119]
Moleskiing	e-tourism	Trust	Web-based	Individual	2005	[120]
MASTROCARONTE	e-tourism	KB, Context-aware	Mobile-based	individual	2003	[121]
SPETA system	e-tourism	Social networks, Semantic Web, Context-aware	Mobile-based	Individual	2009	[122]
Traveller	e-tourism	CB, CF, Demographic information	Web-based	Individual	2009	[123]
Tag recommender system	e-resource	CF	Web-based	Individual	2011	[124]
FolkRank	e-resource	CF, CB	Web-based	Individual	2006-2007	[125, 126]
Tag recommender system	e-resource	CF	Web-based	Individual	2009	[127]
PTV	e-resource	CB, CF	Web-based	Individual	2000	[128]
TiVo	e-resource	Clustering, CF	TV-based	Individual	2004	[129]
TV recommender system	e-resource	Information retrieval clustering	TV-based	Individual	2010	[130]
MBCF-based program RS	e-resource	CF	TV-based	Individual	2011	[131]
queveo.tv	e-resource	CB, CF	TV-based	Individual	2010	[132]
TV program RS	e-resource	Bayesian classifier, Decision tree	TV-based	Individual	2004	[134]
AVATAR	e-resource	Semantic analysis, CB, CF	TV-based	Individual	2006	[135]
AMALTHAEA	e-resource	Information filtering, Information retrieval	Web-based	Individual	1997-1998	[136, 137]
ifWeb	e-resource	CB	Web-based	Individual	1997	[138]
News Dude	e-resource	IR, Bayesian classifier	Web-based	Individual	1999	[30]
Eigentaste	e-resource	CF, Dimensionality reduction	Web-based	Individual	2001	[139]
GroupLens	e-resource	CF	Web-based	Individual	1994-1997	[21, 140]
Foxtrot	e-resource	k-Nearest classification	Web-based	Individual	2002	[141]
WinPUM	e-resource	Graph based clustering	Web-based	Individual	2010	[142]
Web-page recommender	e-resource	Ontology KB	Web-based	Individual	2013	[143]
Lifestyle Finder	e-resource	Demographic information	Web-based	Individual	1997	[144]
ACR News	e-resource	CB, Clustering	Web-based	Individual	2000	[133]
ArgueNet	e-resource	CB	Web-based	Individual	2004	[145]
PocketLens	e-resource	CF, model-based	Web-based	Individual	2004	[146]
CinemaScreen	e-resource	CF, CB	Web-based	Individual	2006	[147]
Flycasting	e-resource	CF	Mobile-based	Individual	2001	[148]
Smart Radio	e-resource	CF	Radio-based	Individual	2001	[149]
RACOFI	e-resource	Semantic Web, CF	Web-based	Individual	2003	[150]
Foafing the Music	e-resource	Social network, CB	Mobile-based	Individual	2005	[151]
CBCF	e-resource	CB, CF	Web-based	Individual	2002	[152]
CoFoSIM	e-resource	Multi-criteria decision-making, CF	Mobile-based	Individual	2010	[153]

I-SPY	e-group		Web-based	Group	2003-2006	[154-156]
GRec_OC	e-group	CB, CF	Web-based	Group	2010	[157]
CAPS	e-group	CB	Web-based	Group	2003	[158]
MusicFX	e-group	CB	Radio-based	Group	1998	[159]
Flytrap	e-group	CB	Radio-based	group	2002	[160]
Adaptive radio	e-group	CF	Radio-based	group	2005	[161]
PolyLens	e-group	CF	Web-based	group	2002	[69]
Glue	e-group	CF, TKI	Web-based	group	2009	[162]
Pocket restaurant finder	e-group	CB	Web-based	group	2002	[164]
CATS	e-group	CB, Critiquing synchronous	Web-based	group	2006	[73, 165]
INTRIGUE	e-group	Weighted average	Web-based	group	2003-2005	[163, 166]
PETs	e-group	Demographic-based CB, CF	Web-based	group	2009	[167]
e-Tourism	e-group	Demographic, CB	Web-based	group	2011	[168]
DCOP-based multiagent	e-group	Agent	Web-based	group	2008	[169]
TDF	e-group	Asynchronous	Web-based	group	2004	[72, 170]
FIT	e-group	CB	TV-based	group	2004	[171]
TV4M	e-group	CB	TV-based	group	2006	[172]
TV programme recommender	e-group	Classifier	TV-based	group	2009	[173]

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