World Wide Web (2007) 10:415–441
DOI 10.1007/s11280-007-0019-8

# Analysis and Classification of Multi-Criteria Recommender Systems

**Nikos Manouselis · Constantina Costopoulou**

Received: 30 March 2006 / Revised: 29 September 2006 /
Accepted: 8 January 2007 / Published online: 27 March 2007


**Abstract** Recent studies have indicated that the application of Multi-Criteria Decision Making (MCDM) methods in recommender systems has yet to be systematically explored. This observation partially contradicts with the fact that in related literature, there exist several contributions describing recommender systems that engage some MCDM method. Such systems, which we refer to as multi-criteria recommender systems, have early demonstrated the potential of applying MCDM methods to facilitate recommendation, in numerous application domains. On the other hand, a comprehensive analysis of existing systems would facilitate their understanding and development. Towards this direction, this paper identifies a set of dimensions that distinguish, describe and categorize multi-criteria recommender systems, based on existing taxonomies and categorizations. These dimensions are integrated into an overall framework that is used for the analysis and classification of a sample of existing multi-criteria recommender systems. The results provide a comprehensive overview of the ways current multi-criteria recommender systems support the decision of online users.

**Keywords** recommender systems · Multi-Criteria Decision Making (MCDM) · classification

## 1 Introduction

An abundant amount of information is created and delivered over electronic media. Users are often becoming overwhelmed by the flow of information, and they are in need of adequate tools to help them manage this situation [34]. An interesting aspect of such

N. Manouselis (✉) · C. Costopoulou
Informatics Laboratory, Division of Informatics, Mathematics & Statistics, Department of Science, Agricultural University of Athens, 75 Iera Odos str., 118 55 Athens, Greece
e-mail: nikosm@aua.gr

C. Costopoulou
e-mail: tina@aua.gr

occasions is that when people engage in information-seeking behavior, it is usually because they are hoping to resolve some problem, or achieve some goal, for which their current state of knowledge is inadequate. This suggests that they don't really know what might be useful for them, and therefore they may not be able to specify the salient characteristics of potentially useful information resources. It has been therefore considered appropriate to provide some kind of recommended action to the information seekers, helping them to better understand their information needs and to use the available information resources more effectively [8]. Recommender systems have been introduced to fulfill this need, attracting high research interest and witnessing an abundance of real-life applications that may help Internet users to deal with information overload. The application domains in the World Wide Web range from recommendation of commercial products such as books, CDs and movies, to recommendation of more complex items such as quality methods and instruments [64].

In a recommender system, the items of interest and the user preferences are represented in various forms, e.g. using a single or multiple attributes for describing an item. Particularly in systems where recommendations are based on the opinion of others, it is crucial to take into consideration the multiple criteria that affect the users' opinions in order to make more effective recommendations. Although recommender systems have already been engaging multiple attributes for the production of recommendations, research about the ways Multi-Criteria Decision Making (MCDM) methods can facilitate the process of creating a recommendation may be still considered sporadic. For example, Adomavicius & Tuzhilin [3] state that MCDM methods have been extensively studied in the Operations Research domain, but their application in recommender systems has yet to be systematically explored. This observation partially contradicts with the fact that in the literature, there are several proposals for recommender systems that use MCDM methods. Such systems may be referred to as *multi-criteria recommender systems*. They have early demonstrated the potential of applying MCDM methods to facilitate recommendation, in numerous application domains (e.g. [28, 74, 79, 91]). On the other hand, a study of existing multi-criteria systems is still missing from the area of recommender systems. Towards this direction, the present paper aims to provide an analysis and classification of multi-criteria recommender systems for the World Wide Web. More specifically, the contributions of this paper are the following:

- To identify the dimensions that are proposed by existing taxonomies and/or categorizations of recommender systems, and to classify them into a concrete set of dimensions that can be used for studying such systems.
- To enhance the collected set of dimensions with dimensions related to multi-criteria recommendation, and to formulate an overall framework that may also be used for the study of multi-criteria recommender systems.
- To provide an analysis and classification of 37 existing multi-criteria recommender systems, according to the proposed framework.

The rest of the paper is structured as it follows. Section 2 presents definitions of recommender systems, introduces their most widely known types, and describes representative approaches for their categorization. Section 3 collects and categorizes important classification dimensions that related studies have identified. In Section 4, the recommendation decision problem is modeled as a MCDM one. The classification dimensions are thus enhanced, leading to an overall framework that may be used for distinguishing, describing and categorizing multi-criteria recommender systems. Section 5 illustrates how the proposed framework is used for an analysis and classification of existing multi-criteria recommender systems. Section 6 provides a discussion of issues and trends in multi-criteria recommendation. Finally, the conclusions of this study and directions for future research are drawn.

## 2 Recommender systems

### 2.1 Definitions

In 1987, Malone et al. [59] provided an overview of intelligent information sharing systems, referring to a fundamental categorization of systems that generally support access to highly dynamic information resources [7, 9, 34, 105]. More specifically, they distinguished two categories: (1) *cognitive filtering* systems as the ones that characterize the contents of an information resource (shortly referred to as an *item*) and the information needs of potential item users, and then use these representations to intelligently match items to users; and (2) *sociological filtering* systems as the ones that are working based on the personal and organizational interrelationships of individuals in a community. Early information sharing systems belonged to the first category and were based on text-based filtering, which works by selecting relevant items according to a set of textual keywords [49]. Recommender systems were introduced as representatives of the second category, being defined as systems that "... help people make choices based on the opinions of other people." [29]. They addressed two problems of text-based systems:

- The problem of overwhelming numbers of on-topic items (ones that would be all selected by a keyword filter), which has been addressed by the introduction of a further evaluation of the items, based on human judgments regarding their quality.
- The problem of filtering non-text items, which has been addressed by judging items solely upon human taste and not their textual descriptions.

The term 'recommender systems' first described systems where "... people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients." [86]. During the time, it evolved to its today's meaning, which covers "... any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options." [14]. Even though this definition covers also the classic text-based filtering systems, Burke [14] states that two criteria distinguish recommender systems from text-based ones: the criterion of 'individualized' and the criterion of 'interesting and useful' content. Table 1 provides an overview of the most interesting definitions that we have identified in the literature, and demonstrates how they have evolved with time.

### 2.2 Types

In the literature, recommender systems have been usually classified into two basic types, according to the way recommendations are made [3, 6, 65, 68, 105, 108, 110]:

- *Content-based recommendation*, in which the information needs of the user and the characteristics of the items are first represented in some (usually textual) form. Then, content-based recommendation uses these representations in order to predict a user's interest in new items [77].

**Table 1** Overview of definitions related to recommender systems.

| Source | Definition | Year |
|---|---|---|
| [29] | "Collaborative filtering simply means that people collaborate to help one another perform filtering by recording their reactions to documents they read." | 1992 |
| [85] | "Collaborative filters help people make choices based on the opinions of other people." | 1994 |
| [97] | "Social information filtering essentially automates the process of 'word-of-mouth' recommendations: items are recommended to a user based upon values assigned by other people with similar taste." | 1995 |
| [86] | "In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients." | 1997 |
| [78, 30] | "The term 'collaborative filtering' describes techniques that use the known preferences of a group of users to predict the unknown preferences of a new user; recommendations for the new users are based on these predictions. Other terms that have been proposed are 'social information filtering' and 'recommender system'." | 1999 (and 2001) |
| [22] | "In collaborative filtering, entities are recommended to a new user based on the stated preferences of other, similar users." | 2000 |
| [93] | "Recommender systems use product knowledge—either hand-coded knowledge provided by experts or 'mined' knowledge learned from the behavior of consumers—to guide consumers through the often-overwhelming task of locating products they will like". | 2001 |
| [14] | "Recommender systems represent user preferences for the purpose of suggesting items to purchase or examine...(the term describes) any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options." | 2002 |
| [49] | "Recommender systems use the opinions of members of a community to help individuals in that community identify the information or products most likely to be interesting to them or relevant to their needs." | 2004 |
| [36] | "Recommender systems use the opinions of a community of users to help individuals in that community more effectively identify content of interest from a potentially overwhelming set of choices." | 2004 |
| [25] | "Recommender systems—a personalized information filtering technology used to either predict whether a particular user will like a particular item (prediction problem) or to identify a set of $N$ items that will be of interest to a certain user (top-$N$ recommendation problem)." | 2004 |
| [33] | "Recommender system is a system that helps users to find their wanted items by making recommendations based on either the content of the recommended items (content-based filtering), or ratings of similar users on the recommended items (collaborative filtering)." | 2004 |
| [39] | "A personalized recommendation system can provide one-to-one service to customers based on customers' past behavior and through inference from other users with similar preferences. The aim of personalization is to offer customers what they want without asking explicitly and to capture the social component of interpersonal interaction." | 2005 |
| [47] | "A recommender system is a typical software solution used in e-commerce for personalized services. It helps customers find the products they would like to purchase by providing recommendations based on their preferences, and is partially useful in e-commerce sites that offer millions of products for sale." | 2005 |
| [94] | "Recommender systems suggest items of interest to users based on their explicit and implicit preferences, the preferences of other users, and user and item attributes." | 2005 |
| [68] | "A recommender system is the information filtering that applies data analysis techniques to the problem of helping customers find the products they would like to purchase by producing a predicted likeness score or a list of recommended products for a given customer." | 2005 |

- *Collaborative recommendation*, in which the user is recommended items that people with similar tastes and preferences liked in the past. Collaborative recommendation (or collaborative filtering) systems predict a user's interest in new items based on the recommendations of other people with similar interests. Instead of performing content indexing or content analysis, collaborative filtering systems rely entirely on interest ratings from the members of a participating community [35].

Moreover, other types of recommender systems have also been proposed in the literature. For instance, Burke [14] distinguishes the following ones (in addition to the two described above):

- *Demographic recommendation*, which classifies the users according to the attributes of their personal profile, and makes recommendations based on demographic classes. An early example is the stereotype-based Grundy system, which has been developed to support book searches in a library [84].
- *Utility-based recommendation*, which makes suggestions based on a computation of the utility of each item for a user, for whom a utility function has to be stored. An example is the advanced search service of the 'EQO: European Quality Observatory' Web portal (http://www.eqo.info).
- *Knowledge-based recommendation*, which suggests items based on logical inferences about user preferences. A knowledge representation (e.g. rules) about how an item meets a particular user need is necessary. An example is the bouquet of services that FindMe provides (http://www.findme.com.ph/).

Furthermore, Adomavicius & Tuzhilin [3] also distinguish recommenders in those that aim to predict *absolute* values of ratings users would give to yet unseen items, from *preference-based* filtering, i.e. predicting the relative preferences of users.

Finally, *hybrid recommendation* has also been identified. Recommender systems of this type combine two or more of the aforementioned types in order to gain better performance and address the shortcomings of each type [14], such as in the cases of Balavanovic & Shoham [6], Claypool et al. [21], Cho & Kim [18], Li et al. [56], and others.

### 2.3 Classification dimensions

The aforementioned broad types of recommender systems provide a general idea about the kind of information that is used in order to produce a recommendation, but do not sufficiently describe other characteristics of such systems. Several researchers have further examined taxonomies and/or classifications of recommender systems, concluding to a number of dimensions upon which recommender systems can be analyzed, described and categorized.

First, in their review of information filtering issues and systems, Hanani et al. [34] presented a high-level framework for the classification of such systems. The proposed framework included dimensions such as the initiative of operation, the location of operation, and the methods for acquiring knowledge from users. Some dimensions of this framework could be specifically used for the description, analysis and categorization of recommender systems.

The review and classification of Schafer et al. [93] focused on the recommender systems of a particular domain, the e-commerce one. Nevertheless, their classification framework (identifying dimensions such as the user inputs, the outputs, the recommendation method, the degree of personalization, and the delivery mode) can be also applied for systems in other application domains. Another survey that focused particularly to the recommender systems of the e-commerce domain has been the one carried out by Wei et al. [111]. The authors also a framework for classifying recommender systems, distinguishing dimensions such as the information used for recommendation decisions, the types of recommendation decisions, and the various recommendation techniques.

As indicated earlier, a survey that focused on the various recommendation techniques, introducing new types of systems apart from the content-based and collaborative ones, has been the one of Burke [14]. His study described in detail the identified recommendation techniques, and compared them in terms of benefits and shortcomings. Furthermore, Montaner et al. [71] focused specifically on recommender agents, and analyzed a number of such systems. Their taxonomy is based on dimensions such as the way the user profile is represented, generated, and adapted to the user preferences. Apart from agent systems, the proposed taxonomy can be used for other, non-agent types of recommender systems as well.

Finally, in their study of recommender systems Adomavicius & Tuzhilin [3] have reviewed the various types of such systems, based on the distinction between content-based, collaborative, and hybrid ones. They provided a very detailed overview of the different techniques used in the context of each system type, in order to support recommendation. All of the above studies, as well as others that did not focus particularly in categorizing recommender systems (e.g. Herlocker et al. [36], Han et al. [33], Perugini et al. [81]), have indicated important dimensions which may be considered for their analysis and classification. In the next section, an integration of proposed dimensions in a number of meaningful categories is attempted.

## 3 Integrating existing approaches for analyzing recommender systems

The dimensions identified from previous studies have been collected, elaborated, and categorized into three main categories: the *rationale*, the *approach* and the *operation* ones. More specifically, the *rationale* category includes:

- ***Supported tasks***. Refer to the dimensions that distinguish recommender systems according to the user tasks that they are meant to support. The main supported tasks may be identified as follows [36]:

  *Annotation in context*. This task occurs when the recommender system is integrated in an existing working environment of the user in order to provide some additional support or information, e.g. a recommendation about the suitability of an item that the user is currently viewing, or links in a Web page that the user is recommended to follow. An example of a recommender that supports such tasks is the one presented by [21].

  *Find good items*. This task refers to suggesting specific items to a user, e.g. presenting a ranked list of recommended items. It has been characterized as the core recommendation task, since it is the task occurring in most systems [36, 105]. Characteristic examples are the top-*N* recommendation algorithms [25].

  *Find all good items*. This task occurs in usage scenarios where the user wants to identify all items that might be interesting. For instance, in databases with large numbers of medical or legal cases, it is very important not to overlook recommending some potentially relevant case, since it may contain crucial information. Such a recommendation service is offered by the EQO Web portal,

where all candidate items are presented to the user, together with a prediction of their suitability [64].
*Receive sequence of items*. This task occurs in usage scenarios where a sequence of related items is recommended to the user, e.g. in entertainment or educational applications. Characteristic application domains are TV programs recommenders (e.g. [98]) and systems providing adaptive sequencing of learning resources (e.g. [13, 43]).

Furthermore, the *approach* category includes three different perspectives. Related research on personalized/adaptive systems (that is, systems that adapt some part of their operation according to the needs or preferences of each particular user) distinguishes the components of such systems in different categories (usually called *layers*). Based on relevant approaches (e.g. [12, 24]) we categorize recommender systems according to the following categories of personalization characteristics:

- ***User model***. The user model (or user profile) refers to the ways that user characteristics are represented, stored and updated in a recommender system. The following dimensions can be identified:

  *Representation*. It can be performed using several *methods* that include [71, 93, 111]: history-based models [29, 55], vector space models [53], semantic networks [69], associative networks [70], classifier-based models [19, 47], user-items rating matrixes [35, 97], demographic features [116], as well as ontologies [66].
  *Generation*. The characteristics related to the generation of the user model are distinguished in the ways of creating the *initial* user model, and the ways of *learning* the model from some collected data [71].

  – The initial user model in a recommender system: (a) may be empty and gradually filled while the user starts interacting with the system; (b) may be manually provided from the user; (c) may be completed according to some stereotype that describes the class in which the user belongs; or (d) may consist of a training set of examples that the user is asked to provide so that the profile can be generated.
  – In some of the above cases, the generation of the user model requires a learning phase, which may engage several techniques to produce the user model from initially collected data, including machine learning, clustering or classification techniques—such as decision trees and rules, case-based reasoning, neural networks, and Bayesian networks [16, 30, 38, 39, 65, 108, 116, 118]. This phase may be also concluded by the application of some dimensionality reduction technique, to limit the size of the user model and thus simplify its processing [30, 55, 94].

  *Update*. After the initial user model is constructed, the recommender system may or may not engage some *method* for updating it, by using an appropriate *technique*.

  – If a method is engaged, it is characterized as being an explicit [54, 98], implicit [19, 55], or hybrid one [6].
  – The techniques used include [57, 59, 68]: (a) manual updating from the users; (b) addition of new information from the interactions of the user with the system; (c) gradual forgetting of outdated information; (d) using of natural selection techniques to identify which user model elements will remain stored

and which will become obsolete; or (e) focusing on particular time-specific intervals of user preferences.

- ***Domain model***. Similarly to the user model, a domain model is required to represent the properties of the items that are being recommended, e.g. the product characteristics in an e-commerce recommender. The following dimensions can be identified:

  *Representation*. The items in the domain may be represented using some *methods* that include: (a) a simple index or a list of items that are all at the same hierarchical level [16, 53, 102]; (b) a taxonomy of items where items belong to a hierarchy of classes of similar items [18, 19, 68]; or (c) an ontology where more complex relationships are defined between items or classes of items [51, 66, 115].
  *Generation*. The descriptions of the items are usually generated using techniques that are beyond the scope of a recommender system. Sometimes though, a recommender system may apply some technique to generate/formulate the appropriate representation from some raw data or other representation that describes the items. Examples of such techniques are association rule mining [110], clustering [115], classification [66], as well as, dimensionality reduction [18].

- ***Personalization***. It refers to dimensions that depict the way that the system provides its recommendations, in terms of:

  *Degree*. The degree of personalization that the recommender system provides [93]. It may be non-personalized recommendations that are the same for all users [102], ephemeral recommendations that are based on immediate or short-term interests of a user [54], or persistent recommendations that take into consideration the long-term interests of the user [29].
  *Method*. The recommendation methods may include [3, 81, 98, 105]: (a) raw retrieval of items where no particular personalization method is engaged and recommended items are presented as results of typical search queries; (b) manual selection of recommendations, for example when some experts, opinion-leaders or celebrities recommend a list of items to all users [119]; (c) demographic or stereotype-based recommendation, where users are classified to pre-defined classes according to their demographic characteristics or user profile [84]; (d) content-based recommendation methods which characterize the contents of the item and the information needs of potential item users, and then use these representations to match items to users [57, 77]; (e) collaborative filtering recommendation methods that recommend items to a user according to what people with similar tastes and preferences liked in the past [35, 50, 97]; as well as, (f) hybrid approaches that combine some of the above methods [6, 14, 21, 105].
  *Algorithm*. Recommendation algorithms can be classified according to their *type* or *technique*:

  – Type may include [3] model-based algorithms [11, 25, 55, 77], memory-based or heuristic-based algorithms [35, 50, 85, 90], instance-based algorithms [105], and hybrid algorithms [78, 87].
  – Algorithms may adopt [93] attribute-based techniques [57, 77], item-to-item correlation techniques [25, 67], or user-to-user techniques [35, 97].

  *Output*. The most common recommendation outputs are [93] suggestions (e.g. 'try this item') [6, 19], original ratings or reviews that other people provided about a particular item [102], or predictions of the ratings that user would give to recommended items [35, 47].

The *operation* category also includes three different perspectives that include dimensions related to the deployment of recommender systems:

- ***Architecture***. It refers to the architecture of the recommender system, which is usually distinguished as [33, 67]:

  *Centralized*. When the recommender system is at one particular location, e.g. in [68].
  *Distributed*. When the system components are distributed to more locations, e.g. in the case of peer-to-peer architectures [33, 67].

- ***Location***. It refers to the location where recommendation is produced and delivered. It can be classified according to the following locations [34]:

  *At information source*. The case when the information source or provider provides a recommender system to its users, e.g. an e-market provides a product recommendation service. The user profile is stored at the information source side. Recommenders of this type include [19, 21].
  *At recommendation server*. Recommendations are provided from a third-party entity, referring to various external information sources, e.g. when restaurants are recommended to interested users by an independent recommender system. The user profile is stored at the recommendation server. Examples include [29, 50, 54].
  *At user side*. The user profile is stored at the user's side, and the recommendations are locally produced, e.g. in the case of an e-mail filtering system. A recommender of this type is [51].

- ***Mode***. It concerns the identification of who initiates the recommendation process, distinguished among [36, 93, 105]:

  *Push mode (active)*. Recommendations are 'pushed' to the user even when the user is not interacting with the system, e.g. via e-mail [29].
  *Pull mode (active)*. Recommendations are produced, but are presented to the user only when he allows or explicitly requests it. Examples include [6, 50].
  *Passive mode*. Recommendations are produced as part of the regular system operation, e.g. as product recommendations when the user visits an e-market [19].

## 4 Enhancing classification dimensions with multi-criteria recommendation

The aim of this section is twofold: first, to address the recommendation problem from the MCDM perspective, and to model it following the steps of a generic decision making methodology; and second, to elaborate the above categorization of classification dimensions, and propose an enhanced set of dimensions that may be used for the analysis and classification of multi-criteria recommender systems.

In related research, the problem of recommendation has been identified as the way to help individuals in a community to find the information or products that are most likely to be interesting to them or to be most relevant to their needs [49]. It has been further refined to the problems of (1) predicting whether a particular user will like a particular item (prediction problem), or (2) identifying a set of $N$ items that will be of interest to a certain user (top-$N$ recommendation problem) [25]. Therefore, the recommendation problem can be formulated as follows [3]: let $C$ be the set of all users and $S$ the set of all possible items that can be recommended. We define as $U^c(s)$ a utility function $U^c(s) : C \times S \to \Re^+$ that measures the appropriateness of recommending an item $s$ to user $c$. It is assumed that this function is not known for the whole $C \times S$ space but only on some subset of it. Therefore, in the context of recommendation, we want for each user c∈C to be able to:

- Estimate (or approach) the utility function $U^c(s)$ for an item $s$ of the space $S$ for which $U^c(s)$ is not yet known; or,
- Choose a set of items $S' \subseteq S$ that will maximize $U^c(s)$:

$$\forall c \in C,\ s = \max_{s \in S'} U^c(s) \tag{1}$$

In most recommender systems, the utility function $U^c(s)$ usually considers one attribute of an item, e.g. its overall evaluation or *rating*. Nevertheless, utility may also involve more than one attributes of an item. The recommendation problem therefore becomes a multi-attribute or multi-criteria one.

In order to model the recommendation problem as a MCDM one, we follow the four steps of Roy's general modeling methodology for decision making problems [89]:

(a) *Object of decision*. That is, defining the object upon which the decision has to be made and the rationale of the recommendation decision.
(b) *Family of criteria*. That is, the identification and modeling of a set of criteria that affect the recommendation decision, and which are exhaustive and non-redundant.
(c) *Global preference model*. That is, the definition of the function that aggregates the marginal preferences upon each criterion into the global preference of the decision maker about each item.
(d) *Decision support process*. That is, the study of the various categories and types of recommender systems that may be used to support the recommendation decision maker, in accordance to the results of the previous steps.

In the next paragraphs, these steps are followed, in order to identify the MCDM dimensions of multi-criteria recommender systems, and to develop an overall framework for the analysis and classification of these systems.

### 4.1 Object of decision

In recommendation, the object of decision is an item $s$ that belongs to the set of all candidate items $S$. To express the rationale behind the decision, Roy [89] refers to the notion of the decision 'problematic.' The four types of common decision problematics identified in MCDM literature, may be considered valid in the context of recommendation:

- *Choice*, which involves choosing one item from a set of candidates;
- *Sorting*, which involves classifying items into pre-defined categories;
- *Ranking*, which involves ranking items from the best one to the worst one; and
- *Description*, which involves describing all the items in terms of performance upon each criterion.

### 4.2 Family of criteria

The set of all candidate items $S$ is analyzed in terms of multiple criteria, in order to model all possible impacts, consequences, or attributes [89, 106]. In recommender systems, the criteria may refer to multiple characteristics of an item (usually the case in content-based recommendation) or to the multiple dimensions upon which the item is being evaluated (the case in collaborative filtering recommendation). This step must conclude to a consistent family of $n$ criteria $\{g_1, g_2, ..., g_n\}$. In MCDM, four types of criteria are formally used [41]:

- *Measurable*, is a criterion that allows quantified measurement upon an evaluation scale.
- *Ordinal*, is a criterion that defines an ordered set in the form of a qualitative or a descriptive scale.
- *Probabilistic*, is a criterion that uses probability distributions to cover uncertainty in the evaluation of items.
- *Fuzzy*, is a criterion where evaluation of items is represented in relationship to its possibility to belong in one of the intervals of a qualitative or descriptive evaluation scale.

### 4.3 Global preference model

Throughout this step, the development of a global preference model provides a way to aggregate the values of each criterion $g_i$ (with $i=1$ ,..., $n$) in order to express the preferences between the different alternatives of the item set $S$. MCDM literature identifies the following categories of preference modeling approaches, which may all be engaged to support recommendation [41]:

- *Value-Focused models*, where a value system for aggregating the user preferences on the different criteria is constructed. In such approaches, marginal preferences upon each criterion are synthesized into a total value using a synthesizing utility function [44].
- *Outranking Relations models*, where preferences are expressed as a system of outranking relations between the items, thus allowing the expression of incomparability. In such approaches, all items are one-to-one compared between them, and preference relations are provided as relations "*a is preferred to b,*" "*a is equally preferred to b,*" and "*a is incomparable to b*" [88].
- *Multi-Objective Optimization models*, where criteria are expressed in the form of multiple constraints of a multi-objective optimization problem. In such approaches, usually the goal is to find a Pareto optimal solution for the original optimization problem [117].
- *Preference Disaggregation models*, where the preference model is derived by analyzing past decisions. Such approaches build on the models proposed by the previous ones (thus they are sometimes considered as a sub-category of other modeling approaches' categories), since they try to infer a preference model of a given form (e.g. value function) from some given preferential structures that have led to particular decisions in the past. Inferred preference models aim at producing decisions that are at least identical to the examined past ones [41].

### 4.4 Decision support process

Recommender systems are the software tools that provide a recommendation, in order to support the users' decision making upon the set $S$ of items. According to the dimensions identified in Section 3, various types of recommender systems may be used to support this decision. To enhance these dimensions with MCDM-related ones, the following additions have been introduced:

- The *rationale* category is enhanced with the *Decision Problematic* dimension, indicating the problematic that the system aims to support (Section 4.1). This dimension may take values from the set [‘Choice,’ ‘Sorting,’ ‘Ranking,’ ‘Description’].
- The *Representation* aspect of both the *User Model* and the *Domain Model* in the *approach* category is enhanced with a *Type* dimension. This dimension may take values from the MCDM criteria types (Section 4.2), and in particular from the set [‘Measurable,’ ‘Ordinal / Features,’ ‘Fuzzy,’ ‘Probabilistic’].
- Also regarding the *Representation* aspect of the User Model, the *Method* dimension is enhanced with values from the MCDM preference modeling approaches (Section 4.3). In particular, its value set is extended to include ‘Value-focused models,’ ‘Outranking relations,’ ‘Optimization models,’ and ‘Disaggregation models.’

Based on the above, an enhanced set of dimensions is developed, which may be used for analyzing and classifying multi-criteria recommender systems. Figure 1 provides the integration of these dimensions into an overall framework, where MCDM-introduced dimensions are denoted in italics. In the next section, we will study the ways existing multi-criteria systems support the recommendation decision.

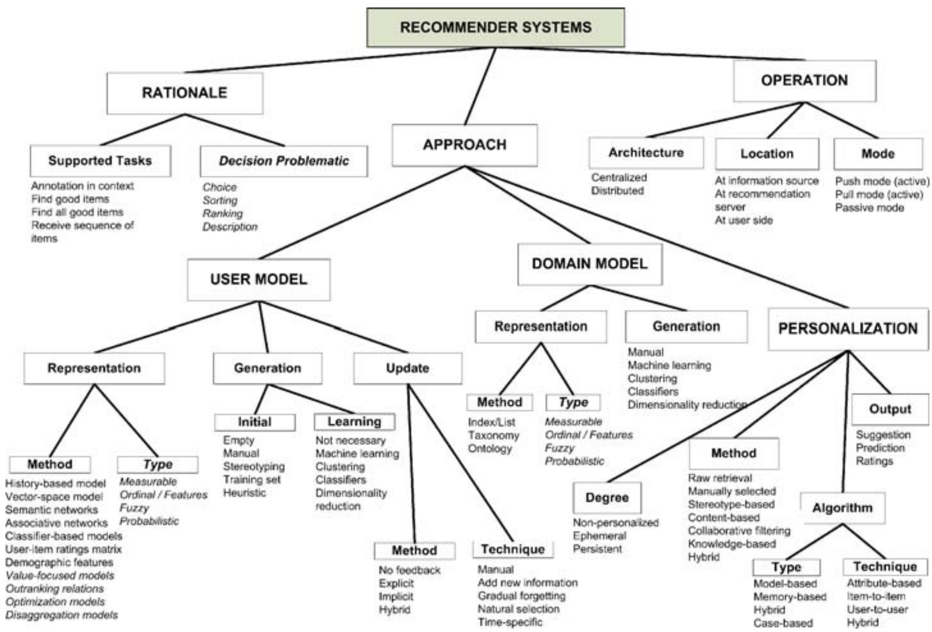


**Figure 1** The proposed framework for the analysis and classification of recommender systems.

## 5 Classification of existing multi-criteria recommender systems

In the following paragraphs, we first present an example of how the proposed framework may be used for analyzing an existing multi-criteria recommender system. Then, the results from the analysis of 37 existing multi-criteria recommender systems are illustrated.

### 5.1 An example

When the proposed framework is used to analyze a recommender system, the system is examined upon each one of the dimensions and is characterized by assigning one (or more, where applicable) of the attributes corresponding to this dimension. To demonstrate how this may take place, we study the case of a characteristic multi-criteria recommender system, the Decision-Theoretic Interactive Video Advisor (DIVA) [74]. DIVA is a collaborative filtering system that provides movie recommendations. It represents user preferences using pair-wise comparisons among items, rather than numeric ratings. It is one of the earlier multi-criteria systems, since it has been introduced in 1998.

Firstly, the *rationale* of the system is examined, using the corresponding dimensions of this category:

- *Supported tasks*. DIVA aims to support the task of finding appropriate movies, and recommends a list of movies when the user requests for it. Thus, it is classified as particularly supporting the 'Find good items' task. From the description of the system, it is inferred that no other recommendation task is supported [74].
- *Decision problematic*. The decision problematic supported is 'Ranking,' since a ranked list of proposed movies is presented to the user.

Secondly, the *approach* that the system adopts is analyzed upon its three sub-categories. Referring to the *user model* aspect, DIVA is classified as:

- *Representation*. The representation of the user model takes place in DIVA by using an 'Outranking relations' *method*. The *type* of user model attributes is 'Ordinal / Features,' since the ordinal evaluation scale {Like, OK, Dislike} is engaged for movie evaluation.
- *Generation*. The *initial* generation of the user model is 'Manual,' since the user has to go through a preference expression process in order to create an initial preference model. To facilitate the generation of the user model, and to create a somewhat accurate user model, DIVA expects from the user to evaluate at least five from the movies in the database. No automatic *learning* method is used for the generation of the user model.
- *Update*. The used *method* of the user model updated is 'Explicit,' as the model changes while the user provides new evaluations. The *technique* followed is 'Add new information,' since the user model is updated incrementally, with the evaluation of new movies by the user.

Referring to the *domain model* aspect:

- *Representation*: DIVA uses an unclassified set of movie features upon which user preferences are denoted, thus the *method* for representation is 'Index/List.' The criteria used include descriptive movie features such as actors/actresses, director, genre, etc., thus the *type* of representation is classified under 'Ordinal/Features.'
- *Generation*: The generation of the domain model is 'Manual' (the creators of DIVA inserted a movie database from the EachMovie data base [74]).

Referring to the *personalization* aspect, the system has been analyzed as it follows:

- *Degree*. The degree of personalization of DIVA is characterized as 'Persistent,' as the system stores the long-term interests of users as well.
- *Method*. The method adopted by the recommendation algorithm of the system is 'Collaborative filtering,' since recommendations are provided based on the similarity of the user preferences to the preferences of other users.
- *Algorithm.* The technique used by the algorithm is therefore 'User-to-user.'
- *Output.* The output is provided in the form of a 'Suggestion' since DIVA predicts only which movies the user may like, and not how much he is expected to like them.

Finally, the DIVA system can be characterized according to the *operation* category of dimensions, as it follows:

- *Architecture.* The DIVA architecture is 'Centralized.'
- *Location*. DIVA is located 'At recommendation server.'
- *Mode.* The operation mode is 'Pull (active),' as the user has to explicitly ask for it, in order for the system to present him with movie recommendations.

## 5.2 Classification results

After an extensive literature review, 37 papers describing multi-criteria recommender systems have been identified. These have been analyzed and classified according to the framework dimensions (Tables 2, 3, 4, 5 and 6). More specifically, in Table 2, multi-criteria systems are classified according to the *rationale* category. From the analysis of the existing approaches, it can be identified:

- *Supported tasks*. The vast majority of the analyzed multi-criteria recommender systems aim to support the task of 'Finding good items.' There have been some applications that aim to support other types of user tasks, but they are still limited. It has been possible to locate only one system for each of the other tasks.
- *Decision problematic*. It can be noted that most recommender systems aim to support the problematic of 'Ranking' alternative items. There are also several systems that support the 'Sorting' problematic, which classifies items into well-defined categories (e.g. appropriate and not-appropriate). A few systems that support the 'Choice' problematic and 'Description' problematic have also been identified.

**Table 2** Classification of multi-criteria recommenders, according to the rationale category.

| Rationale | | |
|---|---|---|
| Supported tasks | Annotation in context | [96] |
| | Find good Items | [5, 17, 20, 27, 28, 31, 37, 42, 45, 46, 48, 52, 54, 58, 63, 72–76, 79, 80, 82, 83, 95, 99–101, 103, 109, 112–114] |
| | Find all good items | [64] |
| | Receive sequence of items | [4] |
| *Decision Problematic* | *Choice* | [5, 27, 48, 52, 54, 83, 103] |
| | *Sorting* | [20, 31, 58, 72, 74, 75, 100, 109, 112–114] |
| | *Ranking* | [4, 28, 42, 45, 46, 63, 64, 73, 76, 79, 80, 82, 95, 99] |
| | *Description* | [17, 37, 96, 101] |

**Table 3** Classification of multi-criteria recommenders, according to the User Model of the Approach category.

| Approach: User Model | | | |
|---|---|---|---|
| Representation | Method | Vector-space models | [4, 17, 54, 109] |
| | | *Value-focused models* | [5, 20, 27, 28, 31, 37, 42, 45, 46, 48, 52, 58, 63, 64, 72, 73, 76, 79, 80, 82, 95, 96, 99, 100, 101, 113, 114] |
| | | *Optimization models* | [83, 103] |
| | | *Outranking relations* | [74, 75, 112] |
| | *Type* | *Measurable* | [5, 20, 27, 28, 31, 45, 46, 52, 54, 58, 63, 64, 72, 73, 76, 82, 95, 96, 99, 100, 103, 113, 114] |
| | | *Ordinal / Features* | [17, 74, 75, 112] |
| | | *Fuzzy* | [37, 42, 79, 80, 101, 109] |
| | | *Probabilistic* | [4, 48, 83] |
| Generation | Initial | Empty | [42, 48, 79, 80, 95, 99, 112] |
| | | Manual | [4, 17, 20, 28, 45, 46, 52, 54, 58, 63, 64, 73–76, 82, 83, 96, 101, 109, 113, 114] |
| | | Stereotyping | [5, 27, 103] |
| | | Training set | [37, 72, 100] |
| | | Heuristic | [31] |
| | Learning | Clustering | [42, 58, 99, 101] |
| | | Classifiers | [45, 46] |
| | | Machine learning | [95, 112] |
| Update | Method | Explicit | [4, 5, 17, 20, 27, 28, 37, 42, 45, 46, 52, 54, 58, 63, 64, 73, 74, 75, 76, 79, 80, 82, 83, 96, 100, 101, 103, 109, 112–114] |
| | | Implicit | [31, 48, 99] |
| | | Hybrid | [72, 95] |
| | Technique | Manual | [4, 17, 20, 27, 28, 42, 45, 46, 52, 54, 64, 63, 73, 76, 79, 80, 82, 83, 96, 100, 101, 103, 109, 113, 114] |
| | | Add new info | [5, 37, 48, 58, 72, 74, 75, 95, 99, 112] |
| | | Natural selection | [31] |

Then, the three aspects of the *approach* category are examined. From the analysis of the *user model* aspect that is illustrated in Table 3, it can be identified:

- *Representation*. Most of the *methods* of the identified multi-criteria recommender systems are based on 'Value-focused models.' This has been somewhat expected, since these models are simpler to conceive and implement. Some systems also use classic 'Vector-space models' with multiple attributes to represent the desired features or the user preferences. Few ones engage some more advanced form of preference modeling, such as an 'Optimization model' or a set of 'Outranking relations.' As far as the *type* of criteria used, most of the examined systems engage 'Measurable' ones. Several also engage 'Fuzzy' or 'Ordinal' criteria for the representation of user preferences, whereas very few use 'Probabilistic' criteria.
- *Generation*. The *initial* user preferences engaged by the examined systems, are usually acquired in a 'Manual' way from the users. In many cases, the user model is initially 'Empty,' and then slowly created throughout the users' interactions with the system. Few multi-criteria recommendation systems use some 'Stereotyping' (demographic) *technique*, some initial 'Training set,' or some other 'Heuristic' method in order to build

**Table 4** Classification of multi-criteria recommenders, according to the domain model of the approach category.

| Approach: Domain Model | | | |
|---|---|---|---|
| Representation | Method | Index/List | [4, 5, 17, 20, 27, 28, 37, 42, 48, 52, 54, 58, 63, 64, 72–75, 79, 80, 82, 83, 96, 99, 100, 103, 109, 113, 114] |
| | | Taxonomy | [45, 46, 101, 112] |
| | | Ontology | [31, 76, 95] |
| | *Type* | *Measurable* | [5, 58, 63, 64, 82, 95, 103] |
| | | *Ordinal / Features* | [4, 17, 20, 27, 28, 31, 37, 42, 46, 45, 48, 52, 54, 72–76, 79, 80, 96, 99–101, 109, 112–114] |
| | | *Probabilistic* | [83] |
| Generation | | Manual | [4, 5, 17, 20, 27, 28, 31, 37, 52, 54, 63, 64, 73–76, 79, 80, 83, 95, 96, 99–101, 103, 109, 112–114] |
| | | Classifiers | [42, 45, 46, 58, 82] |
| | | Clustering | [48] |

the initial user model. In addition, not many systems engage some way (e.g. 'Clustering,' 'Classification' or 'Machine learning') for building the initial model from existing raw data (e.g. transaction history).

- *Update*. In the majority of the systems, the update of the user model is the 'Explicit' *method* and performed by the user. A small number of systems are 'Implicit' and update the model from observing user behavior, or are engaging a combined implicit-explicit method ('Hybrid'). Thus, in the majority of the systems the *technique* used for updating the user model is 'Manual.' Several systems update the user model automatically, as new information about the user actions enters the system ('Add new information').

**Table 5** Classification of multi-criteria recommenders, according to the personalisation of the approach category.

| Approach: Personalization | | | |
|---|---|---|---|
| Degree | | Ephemeral | [4, 17, 20, 27, 42, 45, 46, 52, 54, 63, 64, 96, 100, 101, 109, 113, 114] |
| | | Persistent | [5, 28, 31, 37, 48, 58, 72–76, 79, 80, 82, 83, 95, 99, 103, 112] |
| Method | | Collaborative filtering | [5, 37, 48, 58, 63, 64, 72, 74, 75, 82, 95] |
| | | Content-based | [4, 17, 20, 27, 28, 31, 45, 46, 54, 73, 76, 83, 96, 100, 101, 103, 109, 112–114] |
| | | Hybrid | [42, 52, 79, 80, 99] |
| Algorithm | Type | Model-based | [4, 5, 17, 20, 27, 28, 31, 45, 46, 54, 58, 73–76, 83, 96, 100, 101, 103, 109, 112–114] |
| | | Memory-based | [37, 42, 48, 52, 63, 64, 72, 79, 80, 82] |
| | | Hybrid | [95, 99] |
| | Technique | Attribute-based | [4, 27, 28, 31, 37, 45, 46, 54, 64, 73, 76, 82, 83, 96, 101, 100, 103, 109, 112–114] |
| | | Item-to-item | [20] |
| | | User-to-user | [5, 48, 58, 63, 72, 74, 95] |
| | | Hybrid | [42, 52, 75, 79, 80, 99] |
| Output | | Suggestion | [5, 17, 20, 27, 28, 31, 37, 45, 46, 48, 52, 54, 58, 72–75, 82, 96, 99, 101, 103, 109, 112–114] |
| | | Prediction | [4, 42, 63, 64, 76, 79, 80, 83, 95, 100] |

**Table 6** Classification of multi-criteria recommenders, according to the operation category.

| Operation | | |
|---|---|---|
| Architecture | Centralized | [4, 17, 20, 27, 28, 37, 42, 45, 46, 48, 52, 54, 58, 63, 64, 73–75, 79, 80, 82, 83, 95, 96, 99–101, 109, 113, 114] |
| | Distributed | [5, 31, 72, 76, 103, 112] |
| Location | At information source | [17, 58, 63, 99, 100, 101, 109] |
| | At recommendation server | [4, 5, 20, 27, 28, 37, 42, 48, 52, 54, 64, 73–75, 79, 80, 82, 83, 95, 96, 113, 114] |
| | At user side | [31, 45, 46, 72, 76, 103, 112] |
| Mode | Push (active) | [72, 103] |
| | Pull (active) | [4, 5, 17, 20, 27, 28, 31, 37, 42, 46, 45, 48, 52, 54, 63, 64, 73–76, 79, 80, 82, 83, 95, 96, 99, 100, 109, 112–114] |
| | Passive | [58, 101] |

Only one system applies a 'Natural selection' technique to maintain in the user profile only the information that is judged more important.

Analyzing the collected systems on the *domain model* aspect (Table 4), it can be noted:

- *Representation*. The majority of the *methods* used in multi-criteria recommender systems is a simple 'Index/List' of the items being recommended. Only a few systems (usually e-commerce ones) engage a 'Taxonomy' or an 'Ontology' of items. The *type* of the criteria used for the description of items is usually 'Ordinal/Features' (that is, describing an item using an ordered set of characteristics or features), including systems that use feature-based multi-dimensional representations. Several (mostly value-focused) systems, engage 'Measurable' criteria for the description of the items (e.g. consider multi-attribute ratings of the items in order to produce the recommendation). One system engages a 'Probabilistic' representation of the item attributes.
- *Generation*. As it has been probably expected, the domain model is usually created in a 'Manual' way, since only a few of the recommender systems use some technique to automatically extract item information from existing sources (e.g. product information from e-commerce sites, or movie ratings from text-based reviews).

Similarly, Table 5 presents the analysis of the multi-criteria recommender systems based on the *personalization* aspect:

- *Degree*. Multi-criteria recommender systems are almost equally divided to ones addressing 'Ephemeral' and ones addressing 'Persistent' user needs.
- *Method*. In terms of methods used for the personalization of recommendations, 'Content-based' and 'Collaborative filtering' ones prevail. The content-based systems have been identified to be more than the collaborative filtering ones, and only a few 'Hybrid' approaches currently exist.
- *Algorithm*. The algorithms used in multi-criteria recommenders are mainly 'Model-based,' although many 'Memory-based' ones exist as well. There are also some 'Hybrid' algorithmic approaches. As far as the engaged techniques, most algorithms seem to be employing 'Attribute-based' ones. Very few 'User-to-user' correlation approaches have been proposed in multi-criteria systems, and only one 'Item-to-item' approach.

- *Output*. The produced output is most of the times in the form of suggested items ('Suggestion'), but there are also systems that try to predict the evaluation that a user would give to the suggested items ('Prediction').

Concerning the *operation* category of dimensions, Table 6 indicates that:

- *Architecture*. The majority of multi-criteria recommender systems have a 'Centralized' architecture. Although this trend is expected to slowly change with the further deployment of Grid computing and peer-to-peer architectures, currently few multi-criteria systems adopt a 'Distributed' architecture.
- *Location*. Recommendations are usually produced 'At recommendation server.' Fewer systems produce them 'At information source' or 'At user side.' The latter type of recommendation systems is probably expected to grow as mobile devices become more popular.
- *Mode*. Until now, the majority of multi-criteria systems provide their recommendations at 'Pull mode.' Very few ones operate at a 'Push mode' or 'Passive mode,' which might be relevant to the user tasks they are supporting. For instance, we expect systems that support the 'Annotation in context' task to be providing recommendations in a 'Passive mode.'

### 5.3 Analysis of the classification results

The classification of the sample of existing multi-criteria recommender systems led to the identification of some interesting observations, which may give indications about the current status and the further development of multi-criteria systems. First, it has been observed that the main task that multi-criteria systems support is 'Find good items.' This has been expected, since this task is reported as the most popular one supported by recommender systems [36]. On the other hand, the nature and capabilities of multi-criteria recommender systems make them particularly suitable for supporting other tasks as well. For instance, in the case of the 'Receive sequence of items' task, a characteristic application where multiple factors affect the user's decision is TV programs' recommendation, and existing systems (e.g. [118]) could further benefit by the introduction of MCDM techniques [43]. In addition, multi-criteria recommender systems could benefit from adopting MDCM techniques that may support other decision problematics apart from the 'Ranking' or 'Sorting' ones. For example, the 'Description' problematic fits particularly well recommenders that aim to support the 'Annotation in context' task, since they allow the system describe the prons and cons of a candidate item that a user views, upon each of its multiple features or attributes.

From the results of the previous sub-section, it has also been noted that the MCDM methods used for the construction of the preference models are mostly 'Value-focused models.' Furthermore, from the systems that have been classified in Table 3 as using value-focused models, the majority is adopting Multi-Attribute Utility Theory (MAUT) and is engaging some linear additive value function for the representation of user preferences. MAUT is a traditional decision making approach, widely applied and convenient to implement. On the other hand, assuming that the preference function is linear restricts the way user preferences are represented. Therefore, alternative value-focused forms should be explored, e.g. the representation of utility using sigmoid functions [15, 32].

It is interesting to note that in most of the examined systems, the generation of the user model has been carried out in a 'Manual' way. For instance, some popular systems demand from users to fully express their preferences upon all the criteria (e.g. as a set of weights). Multi-criteria systems could largely benefit from existing techniques, both from the single-criterion recommendation literature, as well as the MCDM literature. As it has been reported in Section 3, current recommender systems use a variety of techniques, such as machine learning, which help them create the user profile based on a set of training examples. In a similar manner, the Preference Disaggregation approaches mentioned in Section 4.3 can support the formulation of a preference model based on a series of previous decisions. A characteristic example is the UTA method, which allows the extraction of the utility function from a user-provided ranking of known items [40]. The adoption and specialization of similar techniques may be also studied for updating the user model as well, e.g. by monitoring user decisions and appropriately revising the model.

Another interesting observation is the small number of hybrid recommendation methods engaged in multi-criteria systems. Hybrid methods have the advantages of combining the benefits and avoiding the shortcomings of different recommendation methods [14, 105]. In addition, the development of a new kind of recommendation systems, meta-recommendation ones, mandates the further development of hybrid systems. Meta-recommendation systems take as input recommendations from various sources and merge them into meaningful meta-recommendations [92]. Multi-criteria systems are undoubtedly affected by these developments, and ways to combine multi-criteria systems with single-criterion ones have to be further explored. Previous work in this area, such as the design methodology to integrate different algorithms into one system that has been introduced by [105], and the hybrid system of [65] that dynamically selects the most appropriate algorithm according to the characteristics of the application domain, may be the basis for such future work.

A final observation that has been made from the study of multi-criteria systems is that current systems seem to be generally developed having a 'Centralized' architecture, and being located 'At recommendation server.' With the advent of mobile and pervasive computing technologies, this is expected to change. Multi-criteria recommender systems will also have to explore distributed and lightweight forms of development. Nevertheless, the increased requirements that multi-criteria systems pose in terms of technical resources have to be addressed. For instance, extending a product database in order to describe the multiple attributes of all products requires a larger storage space, compared to a traditional single-criterion system. In addition, the implementation of sophisticated multi-criteria algorithms (e.g. ones based in multi-criteria optimization methods) will introduce additional complexity to the system development.

## 6 Discussion

In this section, some important aspects related to future developments in the field of multi-criteria recommender systems are discussed. More specifically, we outline the importance of introducing new MCDM methods to support recommendation, we review methods and tools that could be used to support the evaluation of such systems, and we discuss the issue of interoperability between different recommender systems, as well as how it is related to multi-criteria ones.

### 6.1 MCDM modeling

An important concern is raised by Perny & Zucker [79, 80]: the recommendation problem is a new type of MCDM problem that requires new modeling approaches, which should be different from traditional approaches in the context of individual or group decision making. Traditional decision making either deals with a single decision maker that faces a set of candidate solutions (individual decision making), or several decision makers that face the same decision problem with several candidate solutions, where reaching a consensus among the multiple decision makers is the goal (group decision making) [79]. In recommender systems, an implicit sharing of preferences and experiences between different individual decision makers that face similar decision problems takes place.

As Perny & Zucker state [79], despite the multiplicity of possible advisors, the problem addressed is not a matter of group decision making or negotiation between individuals. On the other hand, it is not either an individual decision making problem, since there are several decision problems that have to be addressed simultaneously, and each individual has influence on the recommendation provided to other individuals. Therefore new MCDM modeling approaches should be proposed and tested for multi-criteria recommendation. These are open issues, currently researched by MCDM researchers (see, for example, the joint project between DIMACS at Rutgers University and LAMSADE at Paris IX—Dauphine University [26]). An attempt to propose a new approach has been introduced by Perny & Zucker [80], who have developed a fuzzy preference structure that links users to items, users to users, and items to items. The fuzzy relations they use, represent predicates such as preference, similarity, and influence. Building upon these preference relations, they propose content-based, collaborative filtering and hybrid algorithms, developed according to their modeling approach.

Engaging MDCM modeling may also allow for the exploration of alternative recommendation forms. For example, instead of recommending a list of items that have the top-*N* utility values, a list of items with the best performance upon specific criteria can be proposed (e.g. 'recommend the e-markets that score best in the Reliability and the Website Design criteria') [1]. The production of such recommendations would call for the use of more complex modeling methodologies, such as combinatorial/multi-objective optimization ones [117]. Typical solutions to solving optimization problems include [3]: finding Pareto optimal solutions; taking linear combinations of the multiple criteria and reducing the problem to a single-criterion one; optimizing the most important criterion and converting all the other to constraints; and consecutively optimizing one criterion at each time, converting the optimal solution to a constraint, and repeating the process for the rest of the criteria.

### 6.2 Evaluation

Evaluation is a core aspect of recommender systems design and deployment. The aspects generally evaluated are the accuracy and the coverage of a system's recommendation algorithms [35]. Nevertheless, Herlocker et al. [36] outlined the importance that other system aspects also have, and proposed the consideration of measures related to the suitability of recommendations to users (e.g. confidence in the recommendation, learning rate, novelty/serendipity), the satisfaction of the users, and the technical performance of the system.

From our study of existing systems, we have noted that most current multi-criteria systems usually remain at a design or prototyping stage of development. Testing methods and tools that may support their systematic evaluation in the context of real-life applications are limited. This calls for more work in the field of multi-criteria systems' evaluation, both in terms of recommendation accuracy and coverage, as well as in terms of other system attributes. In previous work, we have introduced a testing tool that allows for the simulated testing of the accuracy, the coverage and the execution time of multi-criteria recommendation algorithms, under controlled experimental conditions [60]. Since multi-criteria evaluation data sets from real-life applications may not be easily found publicly available [36, 104], only experimental data sets that have been collected through pilot user studies or synthetic (simulated) data sets can be used for this purpose [61]. To facilitate this, the testing tool we have developed allows for the creation and experimentation of synthetic data sets with multi-criteria evaluations, where the data set properties may be defined and manipulated by the user.

On the other hand, recommender systems are highly user-centered systems, and it is important to examine methods to assess the users' experience as well. Apart from traditional usability evaluation methods that deal with the design, appearance, and the ease of use of the system itself [23], it is important to examine aspects such as the acceptance of the system by the users, and how they felt it helped them find the information they were looking for. For instance, van Setten [105] has adopted a technology-acceptance model in order to measure how the users accepted a recommender system. For multi-criteria systems, traditional approaches in the evaluation of decision support systems could also be explored (e.g. [10]).

## 6.3 Interoperability

Interoperability refers to the ability of different systems to inter-operate; that is to cooperate and exchange information in pre-agreed, well-defined formats. In recommender systems, a major issue is achieving interoperability of the information that these systems use as input, as well as the information that they produce as output. This can be elaborated into the following interoperability topics:

- *Interoperability of the recommendation queries*, so that the same query can be populated among different recommender systems. Research has already been focused on this dimension, with the proposal of languages such as the Recommendation Query Language (RQL) [2]. The use of an interoperable query language can prove particularly useful in applications such as meta-recommendation systems, where the query has to be spread among the different recommender systems that feed the meta-recommender with their results.
- *Interoperability of the user and the domain models*, so that they may be exchanged among different systems. Interoperable domain models have already been developed in the context of e-commerce standardization bodies and specification groups (e.g. the UN/CEFACT UNSPSC product and services classification, http://www.unspsc.org/). Additionally, using interoperable user models is critical for distributed and mobile applications, such as the cases where the user stores his personal profile (e.g. preferences, history of ratings, previously provided feedback) in a handheld device. The user is then able to reuse the stored profile in different application domains (e.g. different e-commerce stores): the recommender system operating in a particular domain is able to retrieve useful parts of the stored information in order to provide better recommendations. For example, in previous work we have worked towards the development of a metadata schema that may be used to stored item evaluations (ratings, reviews, etc.) in a structured and reusable format [62].
- *Interoperability of the recommendation results*, so that they may be used as input to other systems. Characteristic examples are hybrid or meta-recommendation systems that combine input from different recommender systems, in order to provide aggregated recommendations to the users. One method for presenting aggregated recommendations

is the OLAP-based method proposed in [2]. The MetaLens and DynamicLens systems also use their own format in order to represent and aggregate recommendations from various sources [92]. To our knowledge though, a commonly accepted format for the representation of structured recommendations, which will be understood by the majority of recommender systems, has not yet been proposed.

In multi-criteria systems, where the amount of information stored, managed and exchanged is usually times increased in comparison to single-criterion ones of the same type, the benefits of storing information in an interoperable format are also multiplied. The topic of interoperability has not been addressed by any system in the examined sample of multi-criteria ones. Some preliminary directions and application scenarios for the area of learning resources' recommendation have been discussed in [107].

## 7 Conclusions

In the recommendation literature, there have been several proposals for systems that engage MCDM methods in order to represent user preferences and produce better recommendations. Such methods have been introduced in the recommender systems' area rather early (around 1999), but yet a comprehensive framework for the study of multi-criteria systems is missing from this area. This paper aims to serve as a roadmap to multi-criteria recommendation, by proposing an overall framework for the analysis and classification of multi-criteria recommender systems, as well as, reporting the results from its application for the study of existing systems. The examined sample of multi-criteria systems does not claim to be exhaustive, since there may be systems which have been not included. Nevertheless, it can serve as a comprehensive overview of representative work in this area.

The analysis and classification of multi-criteria recommender systems revealed that most of the existing systems focus on recommending a list of items to the users letting aside other recommendation tasks, such as annotation in context and recommendation of item sequences. In addition, most multi-criteria systems are developed on centralized architectures and situated at one location. However, we expect that the advances in the field of recommender systems, as well as, the dynamic requirements for multi-channel and adaptive systems, will drive the researchers into exploring new forms of multi-criteria systems. Modern recommender systems are required to operate in peer-to-peer environments, through small-scale and mobile devices, and using a minimum set of computing and storage resources. An interesting direction of work is the design of adaptive recommender systems, which will be able to dynamically select the appropriate recommendation algorithm or variation according to the properties of the application context. Furthermore, interfaces to better explain multi-criteria recommendations have to be explored. User understanding of proposed recommendations is considered as an important topic in recommender systems, and has to be explored in the context of multi-criteria recommenders.

The application of the proposed framework for the analysis of a sample of existing recommender systems has demonstrated its usefulness in the direction of: (a) analyzing the characteristics of a recommender system by assigning values from a specific value set for each dimension, and (b) studying the status and development of a family of recommender systems, which in our case has been the class of multi-criteria ones. Furthermore, it would be particularly useful to elaborate a methodology for the analysis and classification of such systems, based on the proposed framework. This methodology could propose a sequence of steps and stages to improve the analysis process of recommender systems, helping researchers and developers in avoiding misunderstandings or individual interpretations of such systems' characteristics.

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