Knowledge-Based Recommendation Systems: A Survey

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ABSTRACT

Knowledge-Base Recommendation (or Recommender) Systems (KBRS) provide the user with advice about a decision to make or an action to take. KBRS rely on knowledge provided by human experts, encoded in the system and applied to input data, in order to generate recommendations. This survey overviews the main ideas characterizing a KBRS. Using a classification framework, the survey overviews KBRS components, user problems for which recommendations are given, knowledge content of the system, and the degree of automation in producing recommendations.

Keywords: *Advice, Automation, Classification Framework, Decision-Making, Knowledge-Base System, Recommendation Problem, Recommendation System, User Profile*

1. INTRODUCTION

In the past decade, recommendation technology has been a steadily growing domain of research, and a hot topic in the information technology industry. Various applications and domains -such as fraud detection, logistics, e-commerce, transport, environment, energy, health, leisure, etc. -have been benefitting from the use of Recommendation Systems (RS). Such systems help respond to the information overload, being able to provide the user with advice about a decision to make or an action to take, when there may be a great many options to consider. The recommendation, or the advice, is made on the basis of the user's behavior and context, which renders the suggestion customized to the user's requirements.

Several types of recommendation techniques exist today and many are already used in commercial applications. The most commonly used techniques can be classified in three categories: collaborative filtering techniques, content-based filtering techniques

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and hybrid systems (Adomavicius & Tuzhilin, 2005). These RS identify trends among a large number of users. The trends, identified on the basis of the users' behaviors, are then used to classify new users. The resulting classification allows the generation of a recommendation under the hypothesis that users belonging to the same class will have and prefer a similar behavior. Companies like Amazon, Google and Facebook apply these types of recommendation algorithms in order to provide their users with books and movies, information sources and ads, and potential friends suggestions, respectively.

However, while the collaborative filtering technique, the content-based technique and the hybrid technique are popular means for the generation of recommendation, it does not mean they are the perfect. Indeed, they have a number of limitations: the new user problem, the new item problem, the grey sheep problem, limited content analysis, over-specialization, and data sparsity (Adomavicius & Tuzhilin, 2005; Martinez et al., 2008; Ramezani et al., 2008).

A Knowledge-Based Recommendation System (KBRS) distinguishes itself among the various types of RS by applying another technique to produce a recommendation. A KBRS generates recommendations on the basis of the domain knowledge. A user will get a recommendation based on his particular profile and the behavior of other users will not be taken into account at all, or when it is, it will not play a central role in determining the recommendation.

The KBRS can thus be used to address limitations of the common recommendation approaches. When using the knowledge-based approach, no large data set is necessary and the cold-start, new item and the grey sheep problem are thus avoided. Also, because the domain knowledge, on which are based the recommendations, is noise-free the recommendations are more reliable. The only limitation faced by the KBRS is the construction of the knowledge base, which usually is a complicated task that demands considerable domain knowledge, and expertise in knowledge representation.

In spite of the interest in knowledge-based recommendation systems, some questions about them remain unanswered. What are the components of a KBRS? Which features can such a system have? Which features must it have? Which steps are necessary for the design of a KBRS? How to analyze a KBRS? How to compare two KBRSs? How to systematically design a KBRS? The lack of answers to these questions motivated our work here.

The objective of this paper is to propose a classification framework for knowledge-based recommendations systems that distinguishes such systems on the basis of their features. The contributions of this research are twofold. Firstly, the framework aims at facilitating the analysis of existing KBRS. Secondly, the proposal of this paper is intended to facilitate the systematic design of new KBRS.

The rest of the paper is structured as follows. In Section 2, we discuss the most commonly used recommendation techniques and we introduce the elements composing the knowledge-based recommendation methodology. We examine several existing KBRS. Based on the related work, we look at the main steps necessary for the development of a knowledge-based recommendation system in Section 3. Next, we introduce the classification dimensions of our classification framework, followed by the application of our framework to the existing literature, in Section 4 and Section 5 respectively. We discuss the results of the framework application in Section 6. Finally, Section 7 concludes our paper.

2. BACKGROUND

In this Section, we will examine the most commonly used recommendation techniques in more detail; this is followed by a review of the literature on knowledge-based recommendation systems.

2.1. Common Recommendation Techniques

Collaborative Filtering is the most common technique for the recommendation of products to users. The first paper to appear on collaborative filtering dates back to the mid-1990s (Park et al., 2012). Recommendation systems are an answer to information overload. They help users find the right product/service among a large volume of proposed items. Aside from collaborative filtering, recommendations can be generated using different techniques, such as the content-based or the hybrid approaches. However, as mentioned in Section 1, these recommendation techniques have several limitations (Adomavicius & Tuzhilin, 2005; Martinez et al., 2008; Ramezani et al., 2008):

- **Collaborative Filtering:**
    - **New User Problem:** The recommendation system has to learn the user's preferences in order to make reliable recommendations. So, the user needs to rate several items before the recommendations system can start producing recommendations.
    - **New Item Problem:** Because the recommendations are only based on the user's preferences, an item has to be rated by a significant amount of users before it can be recommended.
    - The "grey sheep" problem occurs when a user can be classified in more than one group of users. The similarity of this user with two or more groups is equal which makes the recommendations he will get inaccurate.
    - **Sparsity:** Both ratings and users sparsity can cause problems for the production of accurate recommendations.
- **Content-Based:**
    - **Limited Content Analysis:** A sufficient set of features is required in order to produce recommendations. Also, two different items described by the same set of features will be undistinguishable.
    - **Over-Specialization:** The set of recommended items will be very homogeneous, the items will be very similar to the items the user already rated.
    - **New User Problem:** In order to understand the user's preferences and produce accurate recommendations, a certain number of items need to be rated by the user.

Recommendation systems based on hybrid approaches try to combine two techniques in order to enhance their advantages while trying to avoid their limitations.

KBRS were also introduced to tackle the drawbacks from other techniques. The benefits offered by the knowledge-based systems are (Martinez et al., 2008; Ramezani et al., 2008): the cold-start problem, the new item problem as well as the grey sheep problem are all avoided; no large historical data set is necessary; and the recommendations are more reliable since the domain knowledge is noise-free. Nevertheless, this technique faces one important limitation, namely the knowledge acquisition task. Indeed, the latter is very demanding, which renders the development and the maintenance of the system costly (Martinez et al., 2008; Ramezani et al., 2008).

Recommendation systems are not the only answer to information overload. The Semantic Web offers a wide range of information, and domain ontologies can help manage data. Kim et al. (2011) developed a methodology to generate semi-automatically "*domain ontologies from extracted information on the World Wide Web*" (Kim & Storey, 2011). Xu et al. (2011) have proposed a method "*to automatically identify comparison opinions, extract comparison relations, and display results with the comparison relation maps by mining the volume of consumer opinions posted on the Web*". Individuals are not the only ones who can benefit from the data mining techniques for the Web 2.0. Indeed, companies can also profit from such approaches. For instance, Sommer et al. (2012) developed an approach to analyze customer sentiments on Twitter. The analysis can lead to a better product development or improved marketing strategies. Also, Zhang et al. (2013) proposed an approach to identify influencers in online social networks. Companies can benefit from this technique to improve their viral marketing strategies.

In the next Section, we will examine the existing literature about knowledge-based recommendation systems.

2.2. Related Work

Knowledge-Based Recommendation Systems have evolved over the years. The main change is observed in the nature of the knowledge base, which originally takes the form of a database, that is, is a collection of organized data items, and gradually becomes more complex over the years.

Among the works considered here, we can identify two main approaches. On the one hand, several knowledge-base recommendations systems apply a case-based recommendation approach. On the other hand, various KBRS apply a technique similar to the content-based approach.

Various authors used a case-based approach as their recommendation technique. Classically, the user enters his problem description. The cases in the case base are then ranked accordingly, and the most appropriate case is retrieved as a solution to the user problem. Khan et al. (2003), Chattopadhyay et al. (2012), Lee et al. (2007), and Yuan et al. (2013) used this technique for the development of their KBRS.

Khan et al. developed MIKAS, a methodology for the development of a case-based diet recommendation system. The output of the recommendation process was a menu corresponding to the user's requirements. If the retrieved case is not considered satisfactory, human experts have to intervene and provide additional knowledge to solve the problem. This additional expert knowledge will then be added to the knowledge base, ensuring its adaptation (Khan & Hoffmann, 2003). Chattopadhyay et al. proposed "*A Case-Based Reasoning System for Complex Medical Diagnosis*". In their work, the authors focused on a particular medical diagnosis, namely, the PMS cases. Once k similar cases are retrieved from the case base, human experts verify if the output cases are satisfactory. If they are, the case base is updated with the new case. Otherwise, the search process is refined (Chattopadhyay et al., 2012). Lee et al. (2007) proposed a case-based music recommendation system which takes into account, not only the "*user's demographics and behavioral pattern*", but also his context, that is the situation the user is placed in. The recommendation generates 15 songs that were the most frequently and most recently listened by the similar users with a similar context; and presents them to the user. Yuan et al. applied a case-based recommendation system to the real-estate domain. The user enters her wish list in the system, that is the desired location, desired price, and desired housing unit property. The recommendation is generated based on a similarity measure of the problem description and the cases in the case base (Yuan et al., 2013).

Some authors used a conversational case-based approach. The conversational part of the systems is used to build the user profile. The recommendation is then generated using a fitness analysis between the user preferences and the knowledge base.

In the Wasabi Personal Shopper proposed by Burke, an item of the database is examined by the user, who responds to the suggestion by a so-called tweak. Based on the user input, another suggestion is formulated. The preferences of the user are discovered as new suggestions are formulated and as new tweaks are provided (Burke, 1999). A similar logic was applied by Göker et al. (2000) for their "Adaptive Place Advisor", a recommendation system for the selection of a destination, for instance, a restaurant. The user interacts with the system. These interactions are the basis for the creation and refinement of a restaurant specification. The latter is then used to retrieve matching restaurants from a database, based on a similarity analysis. Similar to the Wasabi Personal Shopper, Lee (2004a, 2004b) proposes an interactive recommendation system. The main distinction with the Wasabi Personal Shopper lies in the nature of the knowledge base. It is built by acquiring the knowledge of experts and by storing the previous experiences of user-system interactions. The user requirements are gathered by analyzing the user-system interactions. The items in the knowledge base are ranked according to the user requirements. The product corresponding the most to these requirements is recommended to the user. The latter can modify his requests if the suggested item does not satisfy his needs/wants (Lee, 2004a, 2004b). Aktas et al. (2004) developed a system generating recommendations to scientists searching for "resources in order to solve a science problem". The user is asked questions about the characteristics of the resources he is looking for. The system provides ranked cases as answer to those queries.

Various authors used a recommendation technique similar to the content-based approach. A knowledge base and a user profile are built, and a similarity measure is calculated in order to match an item in the knowledge base and the user preferences.

Towle et al. (2000) proposed to use explicit models for both the user profiles as well as the products. Correlations between the users and the product models are then calculated in order to produce a recommendation. Ghani et al. (2002) proposed a recommendation methodology able to infer the semantic features of a product, leading to an enhanced product database. A recommendation is generated as follows. The probability of the presence of an attribute in a browsed product is calculated by the system. The user profile is then built by combining these probabilities for each examined product. The profile evolves as the user browses products. A comparison is made by the system between this evolving profile and the products in the knowledge base. Finally, the closest matching products are then recommended to the user.

Martinez et al. (2008) propose a knowledge based recommender system "With Multigranular Linguistic Information". Two main steps are necessary for the production of a recommendation: the profiling process followed by the recommendation process. First the user gives an example of item satisfying his needs or wants. This example is used to infer his user profile. Then the similarity between the user profile and the items in the knowledge base is calculated to generate the recommendation.

Garcìa-Crespo et al. (2009) proposed a "Social Pervasive E-Tourism Advisor (SPETA)". Ontology-like structures are used for the representation of both the user and the services. The user profile is created using both explicit user-system interaction and the user's behavior. The recommendation is produced by computing the similarity between the user's preferences and services descriptions. Hsu et al. (2009, 2010) propose a reading material recommendation system. The domain knowledge of various experts is elicited in order to propose articles to individual students so that they can train their reading ability. The matching between the user profile and the knowledge is realized through a fitness analysis, comparing the user's preferences (that is the students' preferences) and the characteristics of each article. The proposed recommendation algorithm is based on the results of the fitness analysis. Rosenfeld et al. (2013) proposed a recommendation system combining knowledge-based approach with a learning component. The latter allows the assessment and the update of the system's recommendations to increase its accuracy. The proposed system was applied to an e-commerce website. At first, experts had to assign a similarity value for each pair of items in the system. The first recommendations were thus made on the basis of the expert knowledge. As the system is in use, the historical data, that is the response of customers to the recommendations, were taken into account, in order to improve the user acceptance of the product. Blanco Fernandez et al. (2008) proposed "A Flexible Semantic Inference Methodology to Reason About User Preferences in KBRS". They applied it for the recommendation of TV programs. The knowledge base is a TV ontology. The recommendation is generated by filtering out the irrelevant programs from the ontology, and by extracting the TV programs which are semantically associated with the user preferences. Later, Blanco Fernandez et al. (2011) also explored "Synergies Between Content-Based Filtering and Spreading Activation Techniques in KBRS". They start by creating the user's "Ontology of Interest" by extracting from the domain ontology the instances significant to the user, that is that are closely related to his or her preferences. The recommendation is generated by discovering hidden user preferences. Similarly, Carrer-Neto et al. (2012) proposed a social knowledge-based RS and applied the system to the movies domain. Users add and categorize elements in their profile according to their preferences; and they create links with other users. In doing so, users can manage their profile preferences. The system uses a movie ontology, and gathers data to instantiate this ontology. The recommendation is generated by an analysis of the preferences and the links between users. We can also note that the users can update their profile anytime. Also, Kaminskas et al. (2012) developed a knowledge-based music recommendation system for Places of Interest (POI); the goal of the system is to select music corresponding to the POI. It is"built upon an ontology-based knowledge representation model in the form of a graph/network of semantic entities (concepts) in different domains, and interlinked by semantic relations (properties)" (Kaminskas et al., 2012); and applies a graph-based ranking algorithm on the network to generate recommendations.

Ajmani et al. (2013) proposed an ontology-based recommendation system for a personalized fashion recommendation. More specifically the proposed system generates recommendations about Sarees in two steps. First, the system determines the visual personality of the user, and creates a corresponding naive Bayesian Network. Second, the system produces the recommendation using the ontology for fashion recommendation, given the context of use (the user personality and the occasion).

As we can see, the range of KBRS varies depending mainly on the nature of the Knowledge Base, which influences the recommendation strategy. While some authors propose a knowledge base allowing a (conversational) case-based recommendation technique (Aktas et al., 2004; Burke, 1999; Chattopadhyay et al., 2012; Göker & Thompson, 2000; Khan & Hoffmann, 2003; Lee, 2004b, 2004a; Lee & Lee, 2007; Yuan et al., 2013); other use a knowledge base containing formalized expert knowledge (Hsu et al., 2010, 2009; Rosenfeld et al., 2013), a domain ontology (Ajmani et al., 2013; Blanco-Fernandez et al., 2008, 2011; Carrer-Neto et al., 2012; Garcìa -Crespo et al., 2009; Kaminskas et al., 2012;), or a database (Ghani & Fano, 2002; Martinez et al., 2008; Towle & Quinn, 2000) and apply a similarity measure to generate a recommendation. Despite the differences between the recommendation methodologies, we can identify two common elements to each of the KBRS considered here: a Knowledge Base and a User Profile. Both elements are examined in the following section.

2.3. Components of a Knowledge Base Recommendation System

Although the existing methodologies can vary greatly, some common elements are necessarily present in one form or another. Indeed, apart from a recommendation strategy proper to each methodology, a knowledge-base recommendation system requires also the presence of a knowledge base and of a user profile.

- **Knowledge Base:** The knowledge base is one of the main components of Knowledge-Based Systems (Liao, 2005; Moisan, 2010). Depending on the kinds of KBRS, the nature of the knowledge base varies. Indeed, as we can observe in Section 2, the knowledge of the recommendation system can take the form of a simple data base, or it can contain a domain ontology, formalized (expert) knowledge, or the knowledge can also amount to a case base. The nature of the knowledge base and the recommendation strategy are closely related and influence one another. Indeed, a quantitative content of a knowledge base is paired with a recommendation strategy involving some kind of similarity measure. On the other hand, a qualitative content of the knowledge base is coupled with a recommendation strategy requiring some sort of matching technique.
- **User Profile:** Because a KBRS provides a personalized recommendation to the user, a user profile needs to be created. The content of such a profile depends on the methodology and recommendation strategy considered. Overall, we can say that the profile is composed of the user preferences,

tastes, interests, needs, etc. The information needed for the identification of the user requirements regarding the particular recommendation problem is gathered in his profile. This information can be collected explicitly or implicitly. The former implies for example, questionnaires handed to the users. The latter implies, on the other hand, an analysis of the user behavior over time in order to extract information about his preferences (Adomavicius & Tuzhilin, 2005).

3. KBRS DEVELOPMENT ACTIVITIES

From the Related Work in Section 2, we can observe that the methodologies used for the generation of recommendations are very different. Nevertheless, a pattern in the development activities can be observed. Indeed, we can see that every methodology needs a knowledge acquisition and a user profile definition phases, then some form of similarity calculation phase in order to provide, eventually, a recommendation to the user.

Some authors propose a preliminary step. This step is usually about preparing the data or ensure that all the necessary requirements for the completion of the methodology are satisfied (Hsu et al., 2009, 2010).

However, according to Felfernig et al. (2006), the building of the recommendation knowledge base is the first step when developing an advisor. Some authors do not mention clearly the knowledge acquisition approach used for the building of the knowledge base; but, they do describe the results of the knowledge acquisition step, that is they explain the content of the knowledge base (Burke, 1999; Martinez et al., 2008; Towle & Quinn, 2000).

Other authors give indication on the means and ends of the knowledge acquisition step. Some methodologies make use of knowledge acquisition approaches that are already known to be effective (Hsu et al., 2009, 2010). While others develop and use their own approach (Blanco-Fernandez et al., 2008, 2011; Garcìa-Crespo et al., 2009; Lee, 2004a, 2004b; Rosenfeld et al., 2013).

For the case-based recommendation system, the knowledge acquisition approach amounts to store the known cases into a knowledge base (or case base). A step of knowledge evolution is usually present. The human experts provide explanations on the application of a particular case as the solution to the user problem. These explanations constitute knowledge added to the case base (Aktas et al., 2004; Burke, 1999; Chattopadhyay et al., 2012; Göker & Thompson, 2000; Khan & Hoffmann, 2003; Lee, 2004a, 2004b; Lee & Lee, 2007; Yuan et al., 2013).

In parallel, some sort of user profile needs to be created or the user behavior needs to be modeled. Information about the user has to be collected: his/her preferences, interests, or any other elements characterizing his situation requiring advice.

The calculation/generation of the recommendation varies greatly depending on the methodology considered. When the knowledge base is closer to a regular database, and the composing items are numerical, the recommendation is calculated on the basis of a similarity measure between the item and the user profile (Towle & Quinn, 2000). On the other hand, when the knowledge base consists of previous cases, that is when the knowledge base amounts to a case base, then the recommendation is generated by matching the new case with a known case stored in the case base (Aktas et al., 2004; Burke, 1999; Chattopadhyay et al., 2012; Göker & Thompson, 2000; Khan & Hoffmann, 2003; Lee, 2004a, 2004b; Lee & Lee, 2007; Yuan et al., 2013). Finally, when the knowledge base consists of formalized expert knowledge or a domain ontology, then the recommendation generation depends on the nature of the knowledge. If the knowledge can be subject to quantitative analysis, then a similarity measure is usually applied to provide the user with a recommendation (Blanco-Fernandez et al., 2011; Garcìa-Crespo et al., 2009; Hsu et al., 2010, 2009; Lee, 2004a, 2004b; Martinez et al., 2008). Otherwise, a match is made between the user problem and the stored knowledge to produce advice (Blanco-Fernandez et al., 2008).

We can see that several common steps are often encountered in the methodology for the development of a recommendation system. Among the five stages discovered -the preliminary step, the knowledge acquisition step, the user profile definition step, the similarity calculation/matching step, and the recommendation step -we can identify the first one, that is the preliminary step, as optional. It is not systematically present or it is blended with the knowledge acquisition step or the user profile definition. Apart from this preliminary stage, the other ones are necessarily present in one form or another. Indeed, on the one hand, because we survey the *Knowledge-Based* System, a knowledge acquisition part is inevitable. On the other hand, because we are dealing with *Recommendation* Systems, the user has to be analyzed in order to find out his/her requirements; also, a match between this user and the knowledge previously elicited has to be found in order to generate a recommendation. We can note that the Case-Base Reasoning cycle is known to be *Retrieve-Reuse-Revise-Retain* (Bridge et al., 2005; Smyth, 2007).

4. CLASSIFICATION DIMENSIONS: DEVELOPMENT OF THE CLASSIFICATION FRAMEWORK

In this section, we present our classification framework (Table 1). Each classification dimension will be introduced by two elements, namely a definition and then its attributes. The former will provide a quick explanation of the proposed dimension, while the latter will determine the relevant features of the classification elements. We suggest three classification dimensions constituting the framework:

1. **The Recommendation Problem and Solution:** Describing what the KBRS is supposed to solve and provide, respectively.
2. **The User Profile:** Defining the necessary features for the delivery of a customized recommendation.
3. **The Degree of Automation:** Determining whether human intervention is required, and if yes, to what extent.

4.1. The Recommendation Problem and Solution

4.1.1. Definition

The recommendation problem and solution dimension are determined by the purpose that the recommendation system has in its application domain.

4.1.2. Attributes

1. **Nature of the Knowledge Base:** One of the main components of a Knowledge-Based System is the Knowledge Base (Liao, 2005; Moisan, 2010). As explained above, the

Table 1. Classification framework: Summary

Dimensions	Attributes
Recommendation Problem and Solution	Nature of the Knowledge Base
	Recommendation Strategy
	Content of the Knowledge Base
	Content of the User Profile
User Profile	How?
	When?
Degree of Automation	User Profile Generation
	Recommendation Rules Generation

knowledge base can contain formalized expert knowledge, a domain ontology or can amount to a database. This feature is relevant, because depending on the content of the knowledge base, various recommendation strategy, that is recommendation algorithms, can be implemented.

2. **Recommendation Strategy:** This attribute defines the necessary steps towards the generation of the recommendation, it corresponds thus to the recommendation algorithm. Various kinds of algorithms are proposed by the literature. Also, we can distinguish between algorithms including a similarity measure and algorithms including another type of matching technique, in other words, we can distinguish between recommendations generated quantitatively and recommendations generated qualitatively. The similarity measure computes the degree to which an item corresponds to the user's requirements. Several similarity measures are available and used by the various methodologies.
3. **Content of the Recommendation:** In Section 2, among the various systems considered, we observed various topics of recommendations made to the users. The final suggestion can be about a product or service to buy, a medical diagnosis, a suggestion for reading material, a TV program, etc. We can also note that the outcome of the recommendation problem can take the form of a list of atomic items or only one (and more general and relational) solution. For the former, the list is composed of either the k most similar items (k being an arbitrary number) or all the items having a similarity measure superior to a given threshold.

4.2. User Profile

4.2.1. Definition

We define the user profile as the information about the user that is used in order to generate a *customized or personalized* recommendation. Depending on the methodology, the user requirements can amount to his or her preferences, interests, needs, etc. Another distinction between the methodologies, is the process of the profile definition. The point in time where the user profile is completely defined, as well as the way the information used for the profile definition is collected, differ from one methodology to the other.

4.2.2. Attributes

1. **Content of the User Profile:** The elements composing the user profile are determined according to the content of the knowledge base and the recommendation strategy. Depending on the methodology considered, the user profile can be composed of: a user ID, the user preferences, interests, needs, the characteristics of the user problem, etc.
2. **Definition of the User Profile:** We propose to characterize the definition of the user profile by two features, namely the *How?* and the *When?*, that is, the process leading to the definition of the profile, as well as, the point in time where the profile is complete.
   a. **How?:** Defines how the information needed for the completion of the profile is gathered. Two main possibilities exist. The information can be inferred from the user behavior: her historical data, clicks, previous purchases, etc. Or, the user can be active: she is asked to answer questionnaires, interviews, etc. The implicitness or explicitness of the profile is thus used to distinguish between the methodologies.
   b. **When?:** the user profile can be defined a priori, so that when the recommendation process starts, all the information available regarding the user profile is already gathered. The profile is stored before any step of the recommendation methodology takes place, so the latter only has to analyze it through its strategy to produce a recommendation. The other possibility is the creation of the user profile when it is needed, it is created on the spot and the preferences

of the user are discovered gradually. The definition process occurs while the recommendation process is carried out. This happens, for example, in interactive systems. Because the methodology knows the information required for an accurate recommendation, the user profile will most likely be complete.

4.3. Degree of Automation

4.3.1. Definition

A knowledge base recommendation methodology is composed of several phases, as illustrated in Section 3. Depending on the methodology considered, some human intervention may be required at some of these stages. We consider the degree of automation of the methodology as our final classification dimension. Nonetheless, we do not take the knowledge acquisition phase into account for the definition of this classification dimension, since we believe that this phase necessarily involves some kind of human intervention.

By definition:

- ◦ A process is "automated if it works by itself with little or no direct human control" (definition from the New Oxford American Dictionary)
- ◦ A process is "automated if it is made automatic or controlled or operated automatically" (definition from WordNet)

We believe that human intervention, and therefore a lack of automation, can occur during two main phases: during the user profile definition or during the recommendation rules generation (which comprises both the calculation of the similarity measure/the matching and the presentation of the final suggestion to the user).

4.3.2. Attributes

1. **User Profile Generation:** As stated above, the user profile generation can be carried out explicitly or implicitly. The automation degree is thus, low or high, respectively.
2. **Recommendation Rules Generation:** The recommendation can be generated automatically from data. Or, it can require the intervention of human experts. Indeed, a human expert may be asked to give his opinion on the recommendation generated automatically before any suggestion is made to the user. The automation degree is thus, high or low, respectively.

5. THE STUDY OF SOME KNOWLEDGE-BASED RECOMMENDATION SYSTEMS: APPLICATION OF THE CLASSIFICATION FRAMEWORK

In this section, we will analyze the literature introduced in Section 2 through the classification framework presented above. Each methodology will be discussed in light of each attribute of each classification dimension. We should note that the aim of this section is to discuss the related work using the proposed classification dimensions, the goal is not to categorize each methodology according to our classification framework. We start with the methodology proposed by Burke in 1999, and go on with the other methodologies chronologically.

Burke (1999) proposed a methodology where the user interacts with the system to find the desired product: a product is first suggested to the user who responds to it by a tweak; a new suggestion is made accordingly, and so on. The recommendation problem and its solution are here characterized by a knowledge base equivalent to a database, the recommendation algorithm corresponds to an interaction strategy, and the recommendation is a suggestion for a product to buy. As far as the user profile is concerned, we can see that its content coincides with the preferences of the user, it is built gradually through the various system-user interactions. The process of profile definition occurs then explicitly and is completed a posteriori, when the final recommendation is generated. Because the user has to interact with the system, the automation degree associated with it is low, while the recommendation rules are automated.

In the methodology proposed by Towle et al. (2000), the recommendation is generated by mapping the explicit models of both the users and the products. The elements characterizing the recommendation problem and solution in Towle's methodology are: a database as knowledge base, a recommendation algorithm based on a match between the two models or a correlation measure if the first method does not yield any results, and a final recommendation suggesting a product to buy. Two approaches are used for the definition of the user profile: the user's past behavior can be taken into account, or the user can be actively queried. The profile is composed of the user preferences and his historical data; and this profile is complete a priori, before any step of the recommendation process takes place. Finally, since the user profile can require the active intervention of the user, the user profile definition is not totally automated; contrary to the recommendation rules, which are perfectly automated.

The recommendation problem in the methodology of Göker et al. (2000) is characterized by a knowledge base equivalent to a case base, a recommendation strategy carried out by the calculation of a similarity measure to generate a recommendation about a restaurant. The user profile definition process is realized through the interaction with the user. Hence, the profile is obtained explicitly, and is complete once the recommendation process is over. The user profile contains the user preferences regarding the restaurants and her past interactions with the systems. As far as the degree of automation is concerned, the generation of the recommendation occurs automatically after the query is obtained; but the profile definition process requires the active intervention of the user.

In the methodology proposed by Ghani et al. (2002), the recommendation solution suggests a product (a piece of female apparel) to buy to the user. The knowledge base is composed of the products and their corresponding semantic features. The recommendation strategy consists of comparing "the evolving profile against the products in the knowledge base, which has products classified into the same taxonomy of semantic features, and recommends the closest matching ones". The user profile is inferred from the user behavior, it is thus built implicitly and contains information about the browsing actions of the users. Because the profile definition is a continuous process and evolves over the browsing time, the profile is complete after the recommendation is generated. Both the user profile definition and the rules generation are automatic processes. Neither human experts nor users have to actively and explicitly intervene.

The case-based diet recommendation system proposed by Khan et al. (2003) provides an answer to a new user by querying its case base. If the case base does not generate any solution, an expert has to intervene and new knowledge is acquired. The recommendation is made by matching the new case with a known one. The recommendation problem and solution is defined by a knowledge base equivalent to a case base; a recommendation algorithm based on "a trapezoid-shaped fuzzy scoring scheme against nutrient requirement"; and a recommendation about a diet program proposed to the user. The user profile is constituted by the elements characterizing the user particular condition. It is given by the user upfront. The definition of the user profile is thus characterized by its explicitness and its completeness prior to any stage of the recommendation process. The necessary intervention of the user renders the profile definition nonautomatic. As far as the recommendation rules are concerned, their automation degree can be high or low. Indeed, sometimes some expert intervention may be required if no solution is generated. On the other hand, if the user case produces a solution, then the recommendation process is automated.

Lee (2004a, 2004b) proposed an interactive recommendation system where the recommendation problem involves various products to buy. The final suggestion is provided to the user by implementing an algorithm calculating the rank between the user requirements and the items in the knowledge base. The latter is composed of expert knowledge and previous experiences of user-system interactions. The user profile contains the user initial requirements, as well as the information gathered through the user-system interactions. Hence, the definition of the user profile, which occurs explicitly, is complete at the end of the recommendation process. Because it is an interactive system, the process of profile definition is nonautomatic. Nevertheless, the recommendation rules are generated automatically from data.

The recommendation problem in the methodology proposed by Aktas et al. (2004) is about the delivery of metadata information to SERVOGrid scientists. The recommendation strategy corresponds to the “threshold retrieval method” applied to the SERVOGrid ontology. The user profile is discovered through the repetitive interactions with the user. It is a continuous process where the user has to be active, the user profile is thus defined explicitly and is complete when the final recommendation is generated. The content of the profile is characterized by the needs of the users regarding a particular resources. Because the user is active in the definition of his profile, this process is considered to be carried out manually. On the other hand, the cases presented to the user are automatically generated on the basis of the answers of the users.

Lee et al. (2007) proposed a “Context Aware Case-Based Reasoning in a Music Recommendation System”. The case base represents thus the knowledge base and the recommendation problem is about the suggestion of music to the user. The recommendation algorithm provides a recommendation solution based on a K-Nearest Neighbor (KNN) algorithm. The user profile contains information about the user’s demographics, his behavioral pattern and his current situation, that is his context. The user profile is built without the intervention of the users; and before any step of the recommendation process starts. As far as the automation degree is concerned, we can observe that both the user profile generation and the rules generation are applied automatically.

The methodology proposed by Martinez et al. (2008) involves an interactive process between the user and the system. The user first gives an example of item corresponding to his preferences. The profile obtained this way is then refined by another information provided by the user. The recommendation is made by computing a similarity measure. The recommendation problem is here represented by a knowledge base in the form of a database; the recommendation strategy corresponds to a similarity-based algorithm, which provides a recommendation solution about a product the user could buy. The user profile, which contains information about her preferences about a product, is defined explicitly through the interactions, and is complete once the final recommendation is made. This user-system interaction renders the automation degree of the profile definition process low, while the similarity measure makes the recommendation rules automatically generated.

SPETA, proposed by Garcìa-Crespo et al. (2009), computes a similarity measure in order to produce a suggestion to the user whose profile is built from explicit user-system interaction and past behavior. SPETA aims to provide a recommendation about a tourism service. This recommendation is produced by applying a feature-based similarity algorithm to a knowledge base containing the descriptions of the proposed services in ontology-like structures. The user profile incorporates the user’s interests and preferences regarding several aspects: places to visit, attractions, favorite artists. The process of the profile definition is carried out both explicitly and implicitly, and is complete when the recommendation process starts. The user profile definition is a partially automated process, since it involves both user-system interaction and analysis of past behavior. The rules generation is, on the other hand, perfectly automated through the application of the feature-based similarity algorithm.

Hsu et al. (2009, 2010) propose a methodology for the recommendation of reading material. The recommendation is made through a fitness analysis, while the user requirements are gathered by the experts and the students themselves. In this case, the recommendation problem is described by a knowledge base containing the expert knowledge, the system aims at providing recommendations on reading materials appropriate to the level of student, through the application of an algorithm based on a fitness analysis. The user profiles, containing the student's preferences and level characteristics, are defined by the experts and the students themselves -thus explicitly before any step of the recommendation process starts. As far as the automation is concerned, while the user profile definition process requires the intervention of experts and students, the recommendation algorithm is completely automated.

Rosenfeld et al. (2013) proposed a hybrid RS, combining expert knowledge and a learning component. The recommendation solution suggests a product to the user, based on a similarity measure. The knowledge base contains the initial expert knowledge and the learnt elements. The user profile is inferred from the browsing activity of the customer, and from her reaction to the recommendations. It contains the user preferences regarding the products of the website. It evolves overtime, and it is thus not complete before the recommendation starts. The degree of automation is high for both the user profile and the rules generations.

Blanco Fernandez et al. (2008, 2011) propose a methodology where the user preferences (inferred by the system or given by the user) are explored by, on the one hand, property sequences (Blanco-Fernandez et al., 2008) and on the other hand, by spreading activation techniques (Blanco-Fernandez et al., 2011), so that a recommendation can be made to the given user. The recommendation solution suggests a TV program to the user, by applying respectively, a property sequences based algorithm and a Spreading Activation techniques based algorithm. For both methodologies, the knowledge base corresponds to the TV ontology. As far as the user profile definition is concerned, the process is carried out both explicitly and implicitly and before the first step of the recommendation process happens. The user profile gathers the user preferences about the TV programs. The automation degree of the profile definition can be high if the preferences are only inferred by the system, or low if the preferences are given by the user. On the other hand, the recommendation rules are automatically generated.

The case-based reasoning system proposed by Chattopadhyay et al. (2012) finds a match between a new user case and one stored in the case base, using a search algorithm based on the KNN. The output obtained by the algorithm is then examined by human experts before it is suggested to the user. The recommendation solution is thus here a PMS diagnosis obtained through a recommendation strategy corresponding to a KNN-based search algorithm applied to a case base. The user profile is given by the user and contains the various characteristics that need to be taken into account in the PMS diagnosis. The profile definition process is thus carried out explicitly and before the recommendation process occurs. The automation degree of both the profile definition and the rules generation is low, because of the intervention of the user and some experts, respectively.

Carrer-Neto et al. (2012) proposed a social knowledge-based RS. In the proposed system, the knowledge base amounts to an ontology. The recommendation strategy is based on a similarity measure, and the content of the recommendation is a movie suggestion. The user profile contains information about the preferences of the user, gathered explicitly; and information about the links with other users, gathered implicitly. Since the user can update her profile whenever she wants, the profile is not complete before the recommendation is made. The degree of automation is low for the user profile generation, and high for the rules generation.

Kaminskas et al. (2012) proposed a music recommendation system for POI. The recommendation solution is a music suggestion for a specific place of interest; and the knowledge base takes the form of an ontology. The recommendation strategy is the graph-based ranking algorithm. As far as the user profile is concerned, it contains the user's context, that is the place of interest the user is at the moment. The profile is inferred by the system, and before the recommendation process starts. The degree of automation for both the user profile generation and the rules generation is high.

Ajmani et al. (2013) proposed an ontology-based fashion recommendation system. The recommendation solution is thus a customized garment recommendation. The knowledge base is an ontology. And the recommendation strategy is based on the posterior probability. The user profile consists of the user context, that is, the user personality (her physical characteristics) and the occasion for which she wants to wear the particular Saree. The user information is collected both explicitly (the user provides a picture) and implicitly (the occasion can be inferred or explicitly specified by the user). The user profile is complete before the recommendation can be generated. The degree of automation for the user profile is thus low, while for the rule generation it is high.

Yuan et al. (2013) proposed a case-based recommendation system for a real-estate application. In the proposed system, the knowledge base consists of a case base. The recommendation strategy is based on the calculation of a similarity measure; and the content of the recommendation is a home suggestion. The user profile is gathered explicitly and contains the problem description, that is the desired characteristics for the house. The profile is complete before any steps of the recommendation process starts. As far as the degree of automation is concerned, it is low for the user profile generation, and high for the rule generation.

This discussion is summarized in Tables 2, 3 and 4.

6. DISCUSSION

The application of our classification framework shows that the several recommendation methodologies vary greatly regarding the Recommendation Problem & Solution and the User Profile. Indeed, various types of content for the Knowledge Base are encountered, and various algorithms are used to provide a recommendation about, usually, a product or a service to buy. Similarly, the possible values for the user profile definition are well distributed: the profile is created with and without the active help of the users, it is complete before and after the start of the recommendation process and the content of the profile differs among the methodologies. However, we can notice that most of the surveyed methodologies suffer from a lack of complete automation: many methodologies require the intervention, at some point, of an expert or the user himself.

In the Introduction Section, we raised a few unanswered questions: What are the components of a KBRS? Which features can such a system have? Which features must it have? Which steps are necessary for the design of a KBRS? Section 2, that is the analysis of the related work, helped providing answers to those questions. We know that a KBRS is composed of a Knowledge Base, a user profile, and a recommendation strategy. Section 3 expressed the various steps necessary for the development of a KBRS.

The framework and its application provide an answer to the other questions raised in the Introduction: How to analyze a KBRS? How to compare two KBRSs? How to systematically design a KBRS?

The application of the framework to the related work demonstrates the utility of the framework in the analysis and the comparison of two KBRS. Indeed, the classification dimensions are specific enough to distinguish between similar KBRS. We can notice that the value taken by the attributes of the classification dimensions for each methodology vary greatly. This variation renders the classification dimensions interesting for the comparison and analysis of KBRS.

Another possible application is related to the design of knowledge-based recommendation systems. The framework could act as a road map for the design process of a KBRS, identifying the features/components necessary for the development of such a system. The various attributes, features of each classification

Table 2. Survey of some knowledge-based recommendation systems: Summary of the recommendation problem and solution

Authors	Knowled ge Base	Recommendation Algorithm	Content
Burke (Burke, 1999)	Database	Interaction	Product
Towle et al. (Towle & Quinn, 2000)	Database	Similarity	Product
Göker et al. (Göker & Thompson, 2000)	Case Base	Similarity	Restaurant
Ghani et al. (Ghani & Fano, 2002)	Enhanced database	Probability	Apparel
Khan et al. (Khan & Hoffmann, 2003)	Case Base	Fuzzy Scoring Scheme	Diet
Lee (W.-P. Lee, 2004b, 2004a)	Knowled ge Base	Rank	Product
Aktas et al. (Aktas et al., 2004)	Case Base	Threshold retrieval	Resources
Lee et al. (J. Lee & Lee, 2007)	Case Base	KNN	Music
Martinez et al. (Luis Martinez & Espinilla, 2008b)	Database	Similarity	Product
García-Crespo et al. (García-Crespo et al., 2009)	Ontology	Similarity	Tourism
Hsu et al. (Hsu et al., 2010, 2009)	Knowled ge Base	Fitness Analysis	Reading material
Rosenfeld et al (Rosenfeld et al., 2013)	Knowled ge Base	Similarity	Product
Blanco Fernandez et al. (Blanco-Fernandez et al., 2008)	Ontology	Property Sequence	TV program
Blanco Fernandez et al (Blanco-Fernandez et al., 2011)	Ontology	Spreading Activation	TV program
Chattopadhyay et al. (Subhagata Chattopadhyay & Acharya, 2012)	Case Base	KNN	PMS diagnosis
Carrer-Neto et al (Carrer-Neto et al., 2012)	Ontology	Similarity	Movie
Kaminskas et al. (Kaminskas et al., 2012)	Ontology	Graph-Based Ranking Algorithm	Music
Ajmani et al. (Ajmani et al., 2013)	Ontology	Probability	Sarees
Yuan et al. (Yuan et al., 2013)	Case Base	Similarity	Home

dimension could then constitute a checklist researchers could use when designing a new KBRS.

However, even if the application of the framework shows that it can be of use for the analysis of KBRS, the classification dimensions could still be refined; and thus lead to a more precise analysis. Another limitation of the framework is its use for the design of knowledge-based recommendation systems. The framework does provide a road map but it does not give any indication for instance, on which element is more important than others; how much time should be devoted to which element.

7. CONCLUSION

We have discussed in this paper the key ideas in the development of knowledge-based recommendation systems. We listed the important elements composing a KBRS, we reviewed

Table 3. Survey of some knowledge-based recommendation systems: Summary of the user profile definition

Authors	Content	How	When
Burke (Burke, 1999)	Preferences	Explicit	Post
Towle et al. (Towle & Quinn, 2000)	Preferences / History	Both	Prior
Göker et al. (Göker & Thompson, 2000)	Preferences	Explicit	Post
Ghani et al. (Ghani & Fano, 2002)	Preferences	Implicit	Post
Khan et al. (Khan & Hoffmann, 2003)	User Case	Explicit	Prior
Lee (W.-P. Lee, 2004b, 2004a)	Preferences	Explicit	Post
Aktas et al. (Aktas et al., 2004)	Characteristics	Explicit	Post
Lee et al. (J. Lee & Lee, 2007)	History / Context	Implicit	Prior
Martinez et al. (Luis Martinez & Espinilla, 2008b)	Preferences	Explicit	Prior
García-Crespo et al. (García-Crespo et al., 2009)	Preferences / History	Both	Prior
Hsu et al. (Hsu et al., 2010, 2009)	Preferences / Characteristics	Explicit	Prior
Rosenfeld et al (Rosenfeld et al., 2013)	Preferences	Implicit	Post
Blanco Fernandez et al. (Blanco-Fernandez et al., 2008)	Preferences	Both	Prior
Blanco Fernandez et al (Blanco-Fernandez et al., 2011)	Preferences	Both	Prior
Chattopadhyay et al. (Subhagata Chattopadhyay & Acharya, 2012)	User Case	Explicit	Prior
Carrer-Neto et al (Carrer-Neto et al., 2012)	Preferences, Links	Both	Post
Kaminskas et al. (Kaminskas et al., 2012)	Context	Implicit	Prior
Ajmani et al. (Ajmani et al., 2013)	Context	Both	Prior
Yuan et al. (Yuan et al., 2013)	House Characteristics	Explicitly	Prior

the state-of-the-art concerning the knowledge-based recommendation methodologies and inferred the main steps in the development of a KBRS. We have also presented a classification framework for KBRS development methodologies. Our proposed classification framework aims at helping the analysis and the understanding of these development methodologies. The classification dimensions constituting the framework are properties of the surveyed methodologies: the framework identifies the nature of the recommendation problem, the way the user profile definition process is carried out and finally the degree of automation proposed by the methodology. In this regard, we have surveyed the main research literature using our suggested classification framework, and we believe that this survey leads to the analysis -and understanding -of KBRS development methodologies. We have also discussed the practical implications of this classification framework.

We can notice that research in recommendation systems in general, and the knowledge-based recommendation systems in particular, is quite a novel field. Nevertheless, we can also observe a trend in the evolution of the development methodology of the KBRS. Indeed, we start with knowledge base similar to databases, and we build up to a knowledge

Table 4. Survey of some knowledge-based recommendation systems: Summary of the automation degree

Authors	User Profile Generation	Rules Generation
Burke (Burke, 1999)	Low	High
Towle et al. (Towle & Quinn, 2000)	Both	Both
Göker et al. (Göker & Thompson, 2000)	Low	High
Ghani et al. (Ghani & Fano, 2002)	High	High
Khan et al. (Khan & Hoffmann, 2003)	Low	Both
Lee (W.-P. Lee, 2004b, 2004a)	Low	Both
Aktas et al. (Aktas et al., 2004)	Low	High
Lee et al. (J. Lee & Lee, 2007)	High	High
Martinez et al. (Luis Martinez & Espinilla, 2008b)	Low	Both
García-Crespo et al. (García-Crespo et al., 2009)	Both	High
Hsu et al. (Hsu et al., 2010, 2009)	Low	High
Rosenfeld et al (Rosenfeld et al., 2013)	High	High
Blanco Fernandez et al. (Blanco-Fernandez et al., 2008)	Both	High
Blanco Fernandez et al (Blanco-Fernandez et al., 2011)	Both	High
Chattopadhyay et al. (Subhagata Chattopadhyay & Acharya, 2012)	Low	Low
Carrer-Neto et al (Carrer-Neto et al., 2012)	Low	High
Kaminskas et al. (Kaminskas et al., 2012)	High	High
Ajmani et al. (Ajmani et al., 2013)	Low	High
Yuan et al. (Yuan et al., 2013)	Low	High

base with a more sophisticated content: from a domain ontology to expert knowledge. As far as the topic of the recommendation problem is concerned, we can see that the application of the reviewed recommendation methodologies does not vary greatly. Indeed, apart from the case base recommendation systems, the surveyed methodologies are usually applied in order to suggest the users with an actual product or service satisfying his preferences or requirements. The recommendation problem is very often related to a commercial context.

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