COLLABORATIVE FILTERING: THEORETICAL POSITIONS AND A RESEARCH AGENDA IN MARKETING

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Collaborative Filtering: 
Theoretical Positions and a Research Agenda in Marketing

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Abstract:

Collaborative Filtering systems have appeared and developed rapidly over the past decade on the Internet. These recommendation systems allow people to use expressed preferences of thousands of other people in order to find the product they desire based on the level of similarity between tastes. In doing so, they provide not only useful applications, in terms of word-of-mouth – or “word-of-web”, as Rosen has recently suggested – for instance, but also a platform to improve our theoretical understanding of the nature and structure of consumers’ preferences. A research agenda emphasizing the social context of recommendations is presented to illustrate one, among many others, research perspective offered by the development of Collaborative Filtering on the Internet.

JEL Classifications: C11, C63, D11, D12, D83, M31.

Key-words: Electronic Commerce; Collaborative filtering; Recommender Systems; Marketing, Experimentation.
Introduction: Emergence of Collaborative Filtering

The impact of the Internet on markets and marketing practices is now a major – and challenging, if not puzzling – area of research. Among the several new situations or possibilities raised by its development is the possibility for more rapid and more expansive communications but in a virtual world, without face-to-face interaction.

Recommendations are one type of such communication, and an especially important one in marketing and consumer behavior [1]. It is therefore easy to find many web sites where a consumer, in the process of looking for advices prior to a purchase, could find helpful recommendations. Indeed, it is currently acknowledged that the Internet is still, at this stage, mostly used as a source of information rather than a real marketspace [2]. However, understandably, the virtual aspect of the Internet makes it difficult for consumers to assess the trustworthiness of these recommendations; thus, many researchers are currently paying attention to this dimension of the Internet in marketing (for instances: [3], [4])

In this context, the emergence of Collaborative Filtering (CF) appears as a promising type of recommendation system: it relies on a large database of explicit or implicit preferences from a large number of consumers on a given product (books, movies, wine….) which serve to predict the likelihood that a new consumer will like or not a given exemplar of this product category. The evolution of Internet-based CF has been very rapid, starting with applications in the area of Web pages (e.g. how to find useful and interesting web pages based on the behavior of similar users), to eventually generalize over products such as movies (SEPIA Video Guide [5]; Cinemax [6]; EachMovie; MovieFinder; MovieLens), books (barnes&noble.com [7]; Amazon.com), music (Amazon.com; Ringo), toys (Toys “R” Us [8]), restaurants (Entree [9]; Bostondine) and online newspaper (Los Angeles Times [10]; NewsDude). These systems have seemingly succeeded in low-risk content domains (products or services) but are still ignored in high-risk domains such as mutual funds or honeymoon destinations [11].

Various research groups and researchers are currently paying attention to the “hardware” issues, mostly within the Information Systems (IS) sector: for example, what are the advantages
and disadvantages of various CF algorithms? Or what is the optimal size of the database, given the necessity, on one side, of a large number of inputs but also, on the other side, the cost of the computation requirements? These issues will not be addressed as such in this paper. Our goal is to focus more on the validity and reliability of CF systems within a marketing context, and more precisely to pay attention to the following two questions: How do these systems perform when compared to other recommendation sources (e.g. critics) or social systems (e.g. word-of-mouth)? What can we learn about the structure of consumers’ preferences when looking at these preferences in an aggregate perspective, such as allowed by CF?

These two issues will be addressed below, following a first section presenting a brief state-of-the art in the domain of CF. Then, in the third section a research agenda will be sketched, and suggestions for further research at the crossroads of IS and marketing will be provided, in order to avoid another case of technological development that would not fit market expectations.

1. Collaborative Filtering as an Information System

Collaborative filtering (CF) (sometimes called “social filtering” [12], or recommender system, [13]) has appeared over the past decade as one methodology designed to perform recommendations on the Internet. According to Goldberg et al., (2000) [14], Rich (1979) [15] is considered as the first reference on CF, but it is only in 1992 that Goldberg et al. [16] coined the term “collaborative filtering” in the context of a system for filtering emails using binary category flags.

The concept has appeared from convergent research on search browsers, intelligent agents and data mining. Among the first reported algorithms and results were GroupLens [17] and Ringo [12]. The GroupLens team initially implemented a neighborhood-based CF system for rating Usenet articles. They used a 1-5 integer rating scale and computed a distance using Pearson correlations. The Ringo system, designed for music recommendations, tested a number of measures of distance between users, including Pearson correlation, constrained Pearson correlation, and vector cosine.
Such a recommendation system is based on three types of inputs: a user \((u)\), an object \((o)\) and a
rating of this object by the user \((r(u, o))\). Typically, in a CF web site, users are asked to tell
about their evaluative opinions on a catalog of items, either books, movies, other web sites, or
any other type of products. These opinions reveal how much a user liked an item. Then the
system compares these profiles with other users’ profiles and finds people with similar
opinions, the neighbors. Then, the system can predict how much the user will like what their
neighbors said they were interested in but that the user has not yet experienced. Based on that,
CF can start recommending new material that the user is more likely to be interested in.

More formally, a recommender system based CF recommends objects \((o)\) to the active user \((u)\)
based on the ratings of \(n\) others users. If we denote the set of all objects as \(O\) and the rating of
user \(u\) for object \(o\) as \(r(u, o)\), the function \(r(u, o): O \rightarrow R\), maps objects to real numbers or to
zero, which means “no rating”. Usually \(R= \{0, 1, 2, 3, 4, 5\} \text{ or } \{0, 1, \ldots, 7\}\), although some
rating systems have or had up to 13 categories (moviecritic.com). We denote the vector of all of
user \(u\)’s ratings for all objects as \(r(u, O)\), and the vector of all of subset of objects that the
active user has rated is \(O-NR\), where \(NR\) is all objects non rated. The vector \(r(u, S)\) is all of
user \(u\)’s ratings for any subset of objects \(S\). Finally, we denote the matrix of all users’ ratings
for all objects as \(r\). In general terms, a collaborative filter is a function \(f\) that takes as input all
ratings for all users, and outputs the predicted ratings for the active user: \(r(a, NR) = f(r(1, O),
\(r(2, O), \ldots, r(n, O)) = f(r)\).

Collaborative filtering is a complex mechanism. The two main aspects of the CF technology are
agents and algorithms. Agents are entities that are capable of taking action on their own, and
algorithms are predefined sequences that agents use to complete a task. Both work in
background to evaluate all the users’ preferences in order to make recommendations for a
specific user. Sometimes, this complex system decides which algorithm is best to accomplish a
specific task for a specific set of data. The entire process of CF based system is structured into
three sub-tasks namely, representation of input data, neighborhood formation, and
recommendation generation, as shown in the figure below.
Figure 1: How collaborative filtering works (adapted from [18])

An important aspect of CF, with respect to the input data, is the critical mass. How many ratings are necessary before a CF system can make a reliable recommendation? To start predicting a new user’s tastes, ten to fifteen ratings from this user are usually enough when the systems-based CF also uses other data, such as the gender, zip code, or age of the end-user, gathered from the registration form each user must fill in to access a Web site [18]. The input data as such is a collection of expressed preferences which is represented by a high- or low-dimensional matrix. The preferences are in fact ratings. A “rating” is a measure of a customer's opinion of a product, service or piece of information. There are explicit and implicit ratings. An “explicit rating” is an opinion expressed directly by the user. More broadly, it can be any type of information that the user gives intentionally to the provider, including answers to questionnaires about personal profile and preferences. Usually expressed in quantitative terms, such as five or seven star rating systems, explicit ratings are the most straightforward method for determining likes and dislikes. Ratings can be either positive or negative.

An “implicit rating” is an opinion inferred from watching user actions. Implicit ratings are the latest trend in collaborative filtering technology. It consists in developing ways of tracking the user’s taste, without customers having to declare officially their preferences. Research shows that implicit ratings can provide effective recommendations [19]. Some useful measures include purchase-related actions and time-related actions (e.g. the time spent viewing an item, placing the item in the customer's shopping basket, etc.). The danger with such ratings is that it
can easily lead to mistakes: sometimes, an active-user might click on the mouse by mistake, or only to show to a friend a website; in other cases, a given web page may be up on the screen for a long time only because the user forgets to close it. An observer may easily misinterpret such behaviors.

With that respect, it is important to point out that, in our perspective, it does make an important difference whether the system uses real ratings and not just observations of past behaviors. Amazon.com CF system, for instance, uses past purchases as inputs to perform predictions, without considering the possibility that these purchases have been made for someone else or that a given purchase has resulted in an unpleasant experience: the book or the record purchased might have not been very satisfying for the consumer. (For some mishaps resulting from confusion between preferences and behaviors, see the example in [20]).

The second component of a CF system is the *neighborhood selection sub-task*. It tries to find the neighbors (neighborhood) which possess two characteristics: they ought to be strongly correlated with the active user, and be able to predict preference for many items not rated by the active user. There are many algorithms used to determine the neighborhood. Pearson correlation-based method, sometimes called “nearest neighbor algorithm”, is the most widely referenced in the literature. The support vector method and a scalable Pearson correlation-based method that uses clustering to improve scalability and accuracy are algorithms that have been studied in the context of the EachMovie data set. Others algorithms used to determine the neighborhood include vector similarity-based methods and graphical models [19].

The recourse to very large databases may nevertheless pose some problems of sparsity, scalability and synonymy. Collaborative filtering based systems are used to evaluate large product sets. Obviously, nobody rates all the items (e.g. all the books available, all the movies available), and this induces technical difficulties to make good correlations. From a statistical point of view, working with sparse matrix of customer’s preferences suppose computational problems, which influences the accuracy of the recommendations. In CF systems like Amazon.com, one can find millions of items to be recommended. A very active customer can only purchase a very small subset of all the books offered through Amazon.com. (For example
1% of 2 million books is 20,000 books.) The determination of the neighborhood (see Figure 1) for the active user requires computation that grows exponentially with millions of customers and products, and CF-based systems will then suffer serious scalability problem. The synonymy problem refers to certain correlations—associations between items—that the system can’t find and may then lead to a different treatment of these items.

The final step of a CF-based recommender system is the recommendation generation, which is based on the determined neighborhood. There are two important methods with that respect [21]: the most-frequent item recommendation, and an association rule-based recommendation. The first method consists in scanning over all products rated in the neighborhood and performing a frequency count. The recommended product is chosen among the most frequent products that have not yet been rated by the active user. The second method is a traditional data mining concept. It consists in finding association rules between a set of co-rated products. More explicitly, the presence of some product in a particular transaction implies that products from the other set are also present in the same transaction.

An important characteristic of a CF system is that it does not seek to dissect the nature or the content of the rating used as input. Thus, CF is different from several other types of recommendation systems, as detailed in Table 1.

<table>
<thead>
<tr>
<th>Type of recommendation system</th>
<th>Description</th>
<th>Examples and references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attribute-based systems</td>
<td>Users are asked to rate the relative importance of a set of predetermined attributes</td>
<td>MovieFinder, CDNow</td>
</tr>
<tr>
<td>Content-based recommender system</td>
<td>Recommend items with similar content to things the user has liked before. These systems use supervised machine learning to induce a classifier that can discriminate between items likely to be of interest to the user and those likely to be uninteresting.</td>
<td>[21], NewsDude [22], [23], Fab [24], ELFI [25]</td>
</tr>
<tr>
<td>Knowledge-based system</td>
<td>Use information about users’ preferences to pursue a knowledge-based approach to generate a recommendation, by reasoning about which products meet the user’s requirements. It has two key components: a database of symbolically represented “beliefs”, and some logically incomplete inference mechanisms.</td>
<td>PersonalLogic, [26], [27]</td>
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</table>
The goal of IF system is to support users in finding relevant information from a dynamic base of data objects. IF systems base their relevance computations on user profiles, and look at the syntactic and semantic content of items to determine which are likely to be of interest or value for a user. [28], [29]

Use content-based recommendation strategies; a user is recommended similar items to those he liked in the past. It is a class of systems adapted from research in case-based reasoning, which have used quantitative decision support tools to get information about users' preferences. Opposed to “knowledge-based recommender system”. [26], [30], CASPER [31], [32], Cool-Tour [33]

Rule-based systems represent knowledge in terms of a bunch of rules that tell you what you should do or what you could conclude in different situations. The knowledge base is represented in the form of if-then rules. The system can keep on expanding the knowledge base by acquiring more domain knowledge with the inference engine. A rule-based recommender system builds profiles passively from observation of users’ behaviors. On the wide spectrum of personalization systems, collaborative filtering can be somehow opposed to rule-based systems because there is a basic philosophical difference between them: a rule-based system is centered on the seller, while collaborative filtering focuses on the buyer. JESS [34], CoolAgent [35], [36], [37]

It should be noticed, however, that, recently, attempts have been made to improve these systems by integrating two or more different approaches within the same recommendation system (see, for instance, [38]). For instance, GroupLens is a hybrid recommendation system combining ratings, data inferred from behaviors and content-based data extracted from the objects under investigation.

The main algorithms used in CF are either based on Bayesian analysis, which models individual preferences as a convex combination of preference factors, or clustering models which simultaneously partition persons and objects into clusters [19], [29]. Breese et al. (1998) [19] found that Bayesian networks, with decision trees at each node, and correlation methods outperform Bayesian clustering and vector-similarity methods. We describe here three algorithms, among the most widely used and the most important.

1.1 Correlation-based predictions

The correlation-based method was originally used in the GroupLens project [17]. It uses Pearson correlations to compute a user's predicted rating of an item. It weights user similarity,
by using all available correlated neighbors, and computed a final prediction by performing a weighted average of derivations from the neighbor’s mean. The predicted rating \( r_{\text{predicted}}(a, o) \) of user \( a \) on item \( o \) is given by:

\[
r_{\text{predicted}}(a, o) = \bar{r}_a + k \sum_{k \neq a} w(a, k)(r_{k, o} - \bar{r}_a),
\]

where \( \bar{r}_a \) is the average rating for active-user, \( k \) is a normalizing factor ensuring that the absolute value of the weights sum to 1; \( r_{k, o} \) is the explicit rating given by user \( k \) on item \( o \). The weights \( w(a, k) \in [-1, 1] \) can reflect distances, correlations, or similarities between user \( i \) and other users that have rated the same items. Most commonly, \( w(a, k) \) is the Pearson correlation coefficient between users \( a \) and \( k \):

\[
w(a, k) = \frac{\sum_j (r_{a,j} - \bar{r}_a)(r_{k,j} - \bar{r}_k)}{\sqrt{\sum_j (r_{a,j} - \bar{r}_a)^2 \sum_j (r_{k,j} - \bar{r}_k)^2}},
\]

where the summations over \( j \) includes items that both user \( a \) and \( k \) have rated in common ([19], [12]). This method has the advantages that it is popular, intuitive, and relatively accurate [19], but it suffers from several limitations such as the fact that the correlation between two users profiles can only be computed based on items that both users have rated.

1.2 Support vector method

Support vector method (SVM) is an alternative approach to the prediction of discrete ratings. It relies on existing expressed preferences to identify ratings classes used to make prediction. The SVM algorithm constructs an optimal margin hyperplane which maximizes the margin between the two classes; then, new “points” (predicted ratings) can be classified by identifying their position on this hyperplane. Support vector method is a statistical approach (see [39]). An advantage of this method is that it guarantees an optimal predicted rating because the solution is the mathematically optimal margin hyperplane. The disadvantage is that the prediction accuracy is affected by the missing data.

1.3 Correlation-based prediction using clusters of users

The idea behind this method is to assemble the users into clusters. This reduces the number of users that are examined for similarity with the active user, and also addresses the scalability
problems. To produce predicted ratings the algorithm treats the clusters as composite users and uses the clusters for determining likely neighbors.

But as mentioned before, the purpose of this paper is not to go further into the computational aspects of CF but rather, on the basis of this presentation of the nature of what is a CF system, to focus on its potential contribution in marketing, and more precisely within a quest to understand important features of consumers’ preferences.

2. Theoretical Positions: The Social Context of Personal Recommendations

The basic idea behind the collaborative filtering (CF) concept is to automate word-of-mouth. People generally decide which movie to see, book to buy, or restaurant to eat at by talking to their friends [1]. Then, they make a decision based on those opinions. The goal of CF is to generate recommendations automatically, and on a large scale, using the Internet as a mean to compile and diffuse others’ evaluations.

CF is said to be an “unprecedented system for the distribution of opinions and ideas and the facilitation of contacts between people with similar interests” [29] (p. 385). The same author also writes that it can be a significant tool in order to increase cross-sells and up-sells, and to deepen customer loyalty, higher sales, more advertising revenues and the increasing the benefit of targeted promotions. But, in our opinion, it does offer more than a strategic advantage: it can lead to important insights into some fundamental issues of consumer behavior. Two of them are detailed below.

The role of personal recommendations in consumer behavior and marketing has always been acknowledged as an important one: word-of-mouth (see for instances: [40], [41], [42]) and opinion leaders (see for instances: [43], [44]) have received lots of attention in the marketing literature and practice. (For an integrated model of word-of-mouth and opinion leadership, see [45]). More recently, the role of critics’ recommendations has been emphasized and studied ([46], [47], [48]). In general, observations and results from research on information sources
used by consumers at the time of a purchase tend to support the idea that social influence is more important than commercial influence [1].

The study of influence, however, is a difficult one. It is not easy to assess the relative importance of various sources of information since most of the time consumers are not aware of the influence mechanisms operating on their decisions, or are reluctant to admit that influence. Recommendations, however, represent a specific type of influence, and may be more easily observed and studied. Ansari et al. (2000) [20] identified five different sources of information available to provide recommendations; they are listed in Table 2 below.

**TABLE 2. Five Information Sources to Provide Recommendations.**

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<tr>
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</thead>
<tbody>
<tr>
<td>1.</td>
<td>A person’s expressed preferences or choices among alternative products;</td>
</tr>
<tr>
<td>2.</td>
<td>Preferences for product attributes;</td>
</tr>
<tr>
<td>3.</td>
<td>Other people’s preferences or choices;</td>
</tr>
<tr>
<td>4.</td>
<td>Expert judgments;</td>
</tr>
<tr>
<td>5.</td>
<td>Individual characteristics that may predict preferences.</td>
</tr>
</tbody>
</table>

But whereas Ansari et al. [20] suggest that many sources of information should be integrated in order to provide better recommendations, our objective is to focus exclusively on the third source, “other people’s preferences or choices”, and to assess its value in predicting accurate choices by consumers.

In such a context, issues such as the level of perceived expertise or even the level of coercive power can affect the consumers’ decision to follow or not “other people’s” recommendations, and, ultimately, impact the level of satisfaction with the recommended product or service. Other determinants affecting the recourse to others’ recommendations include personality traits such as the susceptibility to influence and the need for conformity: bandwagon effects have been documented in various areas [49]. Other researchers have studied the group-induced shifts in individual choice research ([50], [51], [52]). Additional psychological phenomena related to the willingness or reluctance to accept and follow recommendations could be reactance [53] and locus of control [54]. Recently, Tepper (1997) [55] has also paid attention to the search for deliberated nonconformity by some consumers.
All these social influence effects could take us quite far from the basic individual preferences of a single consumer, and indeed examples are easy to find, in daily life, of instances when consumers regret a purchase or are dissatisfied because they have been influenced by factors not relevant to the quality of a product or service (e.g., its current popularity, advertising influences, or pressures from a social group). CF through the Internet allows us to focus exclusively on the similarity of preferences without such “social contamination”: the consumer obtains recommendations to purchase a given product or brand based on his or her own past evaluations and on the basis of the evaluations of a large group of anonymous consumers. Simply stated, it is assumed that the higher the correlation between the tastes of two consumers \( A \) and \( B \), the higher the probability that consumer \( A \) will not appreciate such a new product if consumer \( B \) has not, no matter what type of social relationships exists between the two individuals \( A \) and \( B \).

Another important point from a theoretical perspective is that, in its purest form, CF does not take into consideration the product attributes, as it is the case currently in the dominant research in consumer behavior and economics ([56], [57]). Let us recall that CF is an alternative to content filtering or attribute-based systems which offers recommendations on the basis of preferences for attributes of a product or service. Each type of system bears advantages and disadvantages [20] such as the impossibility to accommodate new products for CF, or the necessity to impose a set of attributes on preferences for content filtering. Since one of our objective is to understand the origins of preferences for products or services for which it is complex to assess (“experiential products”), then CF appears superior to attribute-based systems.

For instance, it may be relatively easy to specify a certain amount of attributes prior to the evaluation of products such as cars or even movies (the genre, the actors, the director, ...). But what about more complex products such as wine, for which only a small group of connoisseurs master the vocabulary necessary to assess the product? Or what about songs? Haute couture and fashion? Jokes? (see Jester [58], a joke recommendation system). Such an approach offers several interesting perspectives: first, will it be possible to find the attributes that are currently
accounted for preferences in experiential products such as movies, for instance, when using a CF system? Second, will a prediction through CF be superior to an attribute-based one? This could lead us to think that CF predictions could be superior also for products easier to decompose into attributes, such as cars or electric appliances. Finally, it should be pointed out that, by relying on CF to understand and predict preferences, we might avoid some dangerous traps in marketing such as “meaningless differentiation” based on “irrelevant attributes” [59].

CF also permits to escape the difficult question of “why” consumers prefer this or that product or brand. On a more practical perspective, the measurement requirements are much more limited and easier to handle than what is currently done in marketing research. It should be pointed out, however, that such an approach is exposed to criticism on several grounds: it overturns the typical scientific approach in which explanation should precede prediction. In doing so, it may lead to a confusion between correlation and causation, a major sin in scientific research.

Still, it is our contention that by focusing exclusively on the impact of “other anonymous people’s evaluations” in providing recommendations, valuable insights can be gained in terms of understanding consumers’ preferences. This is especially the case for so-called “experiential products” for which the identification and evaluation of attributes is difficult for a non-expert (e.g. wine, but also entertainment in movies, music, even jokes…). Identification and knowledge of relevant attributes for products such as wine or art works is usually only possible for experts and only after lots of trials, errors and reflections. The alternative for common consumers who want to make judicious choices may be to rely on the observation of other consumers’ evaluations, and, again, ideally irrespective of any social context that may bias the recommendation process.

Therefore, one of the most interesting promise offered by CF is that by looking at the convergence and divergence of expressed preferences among large group of consumers, some patterns may emerge that might or might not reveal the attributes currently used to assess these preferences in a decompositional way. For instance, for movies, the type of movie (action, romance…) and the actors involved are currently used as determinant factors in predicting
consumers’ evaluations: is this what a CF system analysis will reveal? In other cases, such as art works, the structure of preferences is more difficult to express in terms of attributes (“style”, “subject…”): it would therefore be interesting to observe the patterns of preferences for these highly experiential products.

In a subsequent step, it would be interesting to compare these attributes with those of critics’ who are experts in a domain, and to provide insights into the debate on whether critics are representative of consumers or are social leaders, influencers?

3. A Research Agenda

The goal here is, at least, two-fold: to gain some understanding about the nature of preferences for different products or services, but also to increase one’s ability to predict consumers’ preferences in order to help them to avoid making mistakes in selecting products and services for which they don’t have much experience, for which there is a high level of risk.

Ultimately, the most interesting question from a theoretical point of view is the following: what do we learn by using these correlations between consumers’ expressed preferences that we cannot learn with the more traditional attribute- or content-based models of preferences; could there be one or several latent dimensions in preferences that cannot be expressed otherwise?

However, several other theoretical issues in consumer behavior, with close practical consequences in marketing, could also benefit from further investigation into CF. We present a short list of the most obvious ones below.

3.1. The range of products to study through CF

It is hypothesized that CF is a valid predictor tool for the so-called “experiential” products. For the descriptive information of products, natural language processing is needed. Several categories of information suppose attention and knowledge. For restaurants, it may be important to consider the atmosphere as well as the quality of the cuisine; for wines, descriptions of the flavor sometimes resemble very abstract poetry. With their evocative
language, descriptions of wines are extremely difficult. These questions raise some important issues in consumer behavior and marketing which go back to Nelson (1970) [60] and his distinction between search products, experience products and credence products. Recent developments in consumer behavior research and marketing have also provided valuable insights into experiential consumption. In pursuing this line of investigation, one could shed some light on the nature of these “experiential”, e.g. difficult to decompose into attributes, or, on the contrary, that most products are more or less amenable to a small set of relevant and meaningful attributes. In addition, it is also our belief that this research could shed some light on the debate between the relative benefit of pricemeal evaluations vs. holistic evaluations [61].

3.2 The role of involvement

Until now, the products recommended with CF-based systems have been products that appeal to large number of peoples like movies, CDs, music, books, restaurants, jokes, articles, newspapers, ... All these products have a relatively low price and are not amenable to a trial before the purchase. But what about products such as cars, perfumes or even food? These products are not included in the same category not because CF is not useful for them, but because these products imply “risks”. For example, the high price of a luxury car reduces considerably the number of potential customers. Perfume falls in this category not for its price, but for technical barriers: there is not, until now, systems that can transfer smells at distance. When these systems will be available, perfume will become a product as good as movie for the CF-based systems, for many reasons: accessible price, good diffusion rate, and attributes difficult to identify and which can be evaluated subjectively.

High involvement purchases are those products that are important to the consumer for one or several reasons [62]. Such purchases can be closely tied to the consumer’s ego and self-image. They usually involve some risks for the consumer: financial (highly priced items), social (product important to the peer group), or psychological (the wrong decision might cause some concern and anxiety)[63]. Low involvement purchases are not as important to the consumer, and financial, social, and psychological risks are not nearly as great, translating generally into a limited process of decision-making.
In theory, all types of products can be recommended with CF. If we already have a data base with consumers expressed preferences (ratings) for a product, one can use CF. However, until now, the products recommended through CF are mostly “low involvement purchase decision” which suppose “limited decision-making” (e.g. CDs, jokes), rather than “high involvement purchase decision” products which suppose “complex decision making” (e.g. electronic photography systems, autos).

3.3. The role of expertise
Another interesting research perspective would be to take into consideration the level of consumers’ expertise. For a consumer who does not exhibit a high level of expertise in a given domain, he or she could find it sufficient to compare one’s own preference with that of a small set of critics - assuming that critics condense through experience a wider range of preferences [46] - , instead of comparing one’s preference with a whole database of thousands of consumers’ preferences. In doing so, new insights could be gained with respect to the role of critics in consumers’ decision processes [48].

3.4. The role of culture
Are preferences culturally bounded? What if with a database from the USA one tries to predict the preference of other country consumers? Indeed, CF applications could be aimed at segmenting markets either on a cultural basis or on other socio-demographic or economic dimensions.

3.5. The difference between a CF system based on evaluations and a CF system based on purchases
This point has been mentioned at the beginning of the paper: CF systems like the one used at Amazon.com use past purchases. The question remains: how superior the recommendations and predictions are (or are not) when they rely not (only) on past purchases but (also) on evaluations? In the same perspective, it would be interesting to calibrate the quality of the predictions made by a CF system by comparing the post-purchase satisfaction triggered by a
purchase suggested by an attribute-based model of recommendation versus a CF recommendation.\(^1\)

In summary, at a structural level, a classical consumer’s decision-making process may take the form depicted in Figure 2 below (Figure 2 is an integration of the various comprehensive models of consumer behavior.):

In such a model, the search for information involves extensive reflections and references to previous experiences through the highly fallible filter of memory. It involves the identification of specific attributes to match specific needs. But such an extensive information search is not always possible nor feasible. By integrating a recommender system based CF, the decision-maker does not need to perform an extensive information search process anymore. This process is already encapsulated in the recommender system through the expressed preferences contented in database. In the extreme case where the consumer relies only on CF recommendations for his or her next purchase, the decision-making process takes the form reproduced in Figure 3, with less or no emphasis on memory and no iterations taking place within the information search stage. In reality, consumers are more likely expected to integrate CF within an external search for information, although this also remains to be investigated.
Finally, in addition to the preceding research avenues, other issues of a more practical, operational nature deserve attention: for instance, what is the impact of the measuring scales? What difference does it make to use a 5-point scale versus a 7-point or even a 13-point scale, as MovieCritics was doing?

To answer all these questions we need more than theoretical explanations; we need empirical experimentations in real consumer context decision-making in order to provide, finally, strategies for better recommender systems based-CF.

4. Conclusion

Contrary to most expectations, it appears that Internet and e-commerce calls for more and new intermediaries instead of less; in a universe with more information and a large offering available to consumers, demand may not be the starting point of economic exchanges as it is assumed in traditional marketing models [63]. For a consumer, it may become more difficult to identify his or her own needs and preferences, and the ways to satisfy them, and therefore recommendation systems may benefit and appear more useful. In addition, Internet and related technologies do allow for rapid and highly personalized recommendation system at a low cost.

Internet offers many choices of products, services and content. It becomes more and more difficult for customers to find quickly what they are looking for. In the past, when someone
wanted to read a book or to go to a restaurant, they used to ask their friends whom they knew had about the same taste as them. At a large scale, collaborative filtering concept is an automated version of this word-of-mouth. CF-based system allows people to use expressed preferences of thousands of other people with similar taste to them, and to find the product they are more likely to prefer and enjoy. We show in the table below a synoptic analysis of a CF-based system.

**TABLE 3: Overview of the collaborative filtering characteristics**

<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>• works well for big communities</td>
<td>• no knowledge about the “kinds of items” being filtered can lead incorrect results</td>
</tr>
<tr>
<td>• an automated version of “word of mouth”</td>
<td>• technology cannot utilize additional information about the items even when it may be available and relevant</td>
</tr>
<tr>
<td>• incorporates subjective notions of quality into the filtering process</td>
<td>• feature information used must be relevant to partitioning the item space</td>
</tr>
<tr>
<td>• domain knowledge not needed</td>
<td>• quality dependent on large historical data set</td>
</tr>
<tr>
<td>• quality improves over time</td>
<td>• subject to statistical anomalies in data</td>
</tr>
<tr>
<td>• personalized recommendations</td>
<td>• reacts slowly to changes on preferences</td>
</tr>
</tbody>
</table>

Applications for:
- highly subjective domains (music, travel) and domains where the perceived quality of items fluctuates very widely (e.g., web sites, books, restaurants)

The Internet in general and CF in particular help to build online communities. Companies need communities to make “economies of scale”, in terms of distribution, communication and production. Without communities, we do not have a market place, which implies that we do not have commerce. Furthermore, CF is open for the end-user and allows customers to discover things within an information environment that they probably never would have discovered otherwise. Therefore, it our conviction that CF has a future and that research in this area is promising.

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1 The authors are grateful to one reviewer for suggesting this line of research.