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How to use recommender systems in e-business domains

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Abstract

Recommender systems (RS) were developed by research as a means to manage the information retrieval problem for users searching large databases. Recently they have become very popular among businesses as online marketing tools. Several online companies base their success on these systems, among other conditions. By looking at the last decades, the research on RS can be summarized into two main streams. The first research stream is focused on technical aspects of the algorithms and on identifying new ways to make them more accurate, while the second stream is focused on the effects of RS on customers. Therefore, we can draw several indications from the research on RS about the mistakes that companies should avoid when using RS. In this work we conduct an extensive literature and industrial review and we identify some crucial points managers should mind when developing a RS in order to make it as effective as possible in real world applications, or at least to avoid making it a failure.

Keywords

Personalization; Recommender Systems; E-business; E-commerce

Introduction

The personalization of content on websites became an important research area since appearance of the first papers on collaborative filtering since the mid-1990s (Hill, Stead, Rosenstein, & Furnas, 1995; Shardanand & Maes, 1995). Following these first articles, a new research stream on recommender system (RS) was born. A first definition of the recommender systems has been proposed (Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994) and a first classification of these systems was suggested based on how recommendations are made (namely, content-based, collaborative-filtering and hybrid) (Balabanovic & Shoham, 1997). Over the last two decades, there has been much work done in academia on developing new approaches recommender systems and on extending the aforementioned classification. Several types of algorithms were proposed, such as multidimensional (Adomavicius, Sankaranarayanan, Sen, & Tuzhilin, 2005), conversational (Aha, Breslow, & Munoz-Avila, 2001) and so on. All these algorithms were compared in terms of the main information retrieval accuracy measures (i.e., recommendations' precision and recall or predictions' mean absolute error) by focusing only on improving the of the matching between customers' profiles and recommendations' list. This focus on recommendations' accuracy was due to the fact that these algorithms were developed manage retrieval problems for users searching on large databases.

However it became immediately clear that the adoption of these systems improves not only search-related performance (i.e., time spent to find a relevant item or average rating of the retrieved items) but they also improve business-related performances as customers' trust on the business (Pavlou, 2003), customers' satisfaction and quality (Bharati & Chaudhury, 2004) and firm's sales (Fleder & Hosanagar, 2009). Therefore, much work has been done on finding the existing relations between algorithm characteristics and customers' reactions to recommendations thus shifting the research focus from algorithms to customers' reactions. The interest in this area remains high because it constitutes a problem-rich research area and because of the abundance of practical applications providing personalized recommendations, content and services to users. In addition, the number of firms using recommender systems as part of their business impressively grew up in the last years. Examples of such applications include Facebook (Herbrich, 2012), Yahoo! (Lempel, 2012), Echo Nest (Lamere, 2012), LinkedIn (Amin, Yan, Sriram, Bhasin, & Posse, 2012), Microsoft (Koenigstein, Nice, Paquet, & Schleyen, 2012), Netflix (Amatriain, 2012), eBay (Sundaresan, 2011) and others (Liu, Chen, Cai, & Yu, 2012; Smyth, Coyle, & Briggs, 2012). Furthermore, RS constitute mission-critical technologies in some of these companies. For example, at least 60% of Netflix movie rentals and downloads come from their RS, making it of strategic importance to Netflix (Thompson, 2008).

The increasing number of firms that use recommender systems call scholars to focus their effort on studying business-related issues. While much work has been done on improving and developing more accurate recommender systems and on studying the effects of these tools on customers, very little research has been done on identifying the milestones managers should consider when personalizing their web-sites with recommender systems. In this paper, we conduct an extensive literature review to come up coming up with a list of mistakes managers should avoid when dealing with recommender systems.

Literature Review

The roots of recommender systems can be found in the approximation (Powell, 1982), information retrieval (Salton, 1988), forecasting (Armstrong, 2001) and consumer choice modeling theories (Lilien, Kotler, & Moorthy, 1992). In the most common formulation, the recommendation problem consists of finding the set of items that mostly matches a user profile. More formally, let us consider C to be the set of all S to be the set of all possible items and u to be the function that measures usefulness item s to user c. Then the recommender system has to compute the utility u of each for each user and to select the items that maximize the utility function (Adomavicius Tuzhilin, 2005).

After the first formulations (Hill et al., 1995; Resnick et al., 1994; Shardanand & 1995) of recommendation problem, (Balabanovic & Shoham, 1997) classified the recommender systems into three categories, namely content-based, collaborative and hybrid approaches, based on how recommendations are made. In content-based systems, items that have a high degree of similarity to users' preferred items (inferred through ratings or purchases) are recommended (Mooney & Roy, 2000; Pazzani & Billsus, 2007). An advantage of using content-based designs is that even a small set of users can be addressed effectively. As highlighted by (Shardanand & Maes, 1995) and (Balabanovic & Shoham, 1997), a major limitation of content-based methods is that one must be able to parse items using a machine, or their attributes must be assigned items manually. Unlike content-based recommendation methods, collaborative systems recommend items based on historical information drawn from other users similar preferences (Breese, Heckerman, & Kadie, 1998). Collaborative recommender systems do not suffer from some of the limitations of content-based systems; in fact, since collaborative systems use other users' recommendations (ratings), they can deal with any kind of content and even recommend items from product categories other the ones rated or purchased by a user. However, collaborative filtering suffers from "new item problem", namely the difficulty of generating recommendations for items which have never been rated by users. Both collaborative filtering and content-based systems suffer from the "new user problem", namely the difficulty of generating meaningful recommendations for users who have never expressed any preference (Balabanovic & Shoham, 1997; Lee, 2001). Finally, those who use hybrid approaches are trying to avoid the limitations of content-based and collaborative systems by combining collaborative and content-based methods in different ways (Claypool et al., 1999; Soboroff & Nicholas, 1999).

After these first studies, large amount of literature was focused on developing more effective recommender systems that overcome the limitations of the first engines. In particular, much work has been done on reducing sparsity problem (Sarwar, Karypis, Konstan, & Riedl, 2000), improving scalability (Linden, Smith, & York, 2003), protecting users' privacy (Ungar et al., 1998) or reducing cold-start problems (Massa Avesani, 2007). On the other side, a large amount of literature was focused on extending the aforementioned three approaches and on studying how to include other information besides customers' demographic data, past purchases and past product ratings, in order to improve the accuracy of recommendations. There were proposed clustering algorithms (Ungar et al., 1998), demographic filtering techniques (Pazzani, 1999), knowledge based RS (Burke, 2000), conversational case-based RS (Aha et al., 2001), comparison based RS (McGinty & Smyth, 2003), critiquing based RS (Chen &

Pu, 2006), RS based on expert evaluations (Ansari, Essegaier, & Kohli, 2000) and contextual recommender systems (Adomavicius et al., 2005). Among all these new research streams, context-aware recommender systems were the most investigated and they were also largely considered as the best performing ones. In particular, (Bettman, Luce, & Payne, 1998) demonstrated that context induces important changes in a customer's purchasing behavior. Other experimental research suggested that including context in a user model in some cases improves the ability to predict behavior (Palmisano, Tuzhilin, & Gorgoglione, 2008). (Adomavicius et al., 2005) described a way to incorporate contextual information into recommender systems by using a multidimensional approach in which the traditional two-dimensional (2D) user/item paradigm was extended to support additional contextual dimensions, such as time and location, while (Gorgoglione & Panniello, 2009; Panniello & Gorgoglione, 2012; Panniello, Gorgoglione, & Palmisano, 2009) proposed pre-filtering, post-filtering and contextual modeling approaches and compared these systems among them.

In almost all previous works, the different recommendation engines were evaluated or compared in terms of accuracy metrics such as precision, recall or F-measure (Herlocker, Konstan, Terveen, & Riedl, 2004) and they were also developed aiming at improving only recommendations' accuracy. However, in recent years many scholars focused their attention on designing recommender systems built to improve performance metrics different from the sole accuracy. McGinty and Smyth (2003) investigated the importance of diversity as an additional item selection criterion and demonstrated that the gains can be significant, but they also showed that its has to be carefully tuned. Fleder and Hosanagar (2009) demonstrated that systems that discount item popularity in the selection of recommendable items may increase sales more than recommender systems that do not. Adomavicius and Kwon (2012) showed that while ranking recommendations according to the predicted rating values provides good predictive accuracy, such a system provides poor performance with respect to recommendation diversity. Therefore, they proposed a number of recommendation ranking techniques that can provide significant improvements in recommendation diversity with only a small amount of loss of accuracy. Panniello, Tuzhilin, and Gorgoglione (2014) compared several contextual approaches in terms of both accuracy and diversity thus proposing some interesting guidelines on how to the best performing method.

Recent research has largely demonstrated that recommender systems' goals go far beyond the simple item retrieval. In particular, recommender systems may improve sales (Fleder & Hosanagar, 2009), increase cross-selling (Mild & Reutterer, 2003), avoid customer churn (Wang, Chiang, Hsu, Lin, & Lin, 2009), help new and visitors, build credibility through community, invite customer back, and build long-term relationship (Schafer, Konstan, & Riedl, 2001).Therefore, in recent years a number of studies have attempted to incorporate firm-specific measures into the item selection process and have attempted to place the issue of recommender design within profit-maximizing context. This stream of research is particularly important because recommender systems were conceived as a tool to help consumers select relevant information when browsing the Web but soon became a tool for improving the effectiveness of companies' marketing actions. Bodapati (2008) studied the relevance-profitability tradeoff in recommender design. The author modeled recommendations as marketing actions that can modify customers' buying behavior relative to what they would do without such an intervention. He argued that if a recommender system suggests items that are most relevant, it may be of little value if those items might eventually be bought by consumers in the absence of recommendations. He showed that the system should recommend items with a probability that can be best influenced by the recommendation, instead of recommending a product that is most likely to be purchased. Chen, Hsu, Chen, and (2008) integrated the profitability factor into a traditional recommender system and compared four different systems (obtained by using a personalized/non-personalized system and by including and not including profitability). They showed that including profitability increases the cross-selling effect and revenues and that it does not cause recommendation accuracy to drop. Hosanagar, Ramayya, & Ma (2008) also investigated how to recommend products to help firms increase profits rather than recommend what is most likely to be purchased. The authors identified the conditions under which a profit-maximizing recommender system should suggest an item with highest margin and those under which it should recommend the most relevant item. Similarly, (Das, Mathieu, & Ricketts, 2009) developed a model that uses the output of traditional recommender system and adjusts it based on item profitability. The authors applied a model of consumer response behavior to show that their proposed design achieve higher profits than traditional recommenders. Other studies on profit-based recommenders include works by (Akoglu & Faloutsos, 2010; Brand, 2005; Iwata, Saito, & Yamada, 2008).

The shift of the use of RS as tool to help consumers selecting relevant information browsing the Web to tool for improving the effectiveness of companies' marketing actions, called scholars to investigate on customers' reactions to this kind of actions. Several researchers have studied how users respond to personalized focusing on factors that influence perceived usefulness and ease of use, trust, and satisfaction. Gefen, Karahanna, and Straub (2003), and Pavlou (2003) integrated trust, risk, and perceived usefulness and ease of use and empirically confirmed the links trust to perceived usefulness and adoption intention. Benbasat and Wang (2005) extended the integrated model to online recommender adoption and demonstrated the link between trust and adoption intention. Liang, Lai, and Ku (2007) demonstrated both the number of items recommended to the user and the recommendation accuracy, as measured by the number of recommended items accepted by the user, had a significant effect on user satisfaction. Bharati and Chaudhury (2004) showed that the recommender's information quality (i.e., relevance, accuracy, completeness, and timeliness) had a significant effect on users' decision-making satisfaction. An interesting research stream includes studies of how the diversity and familiarity of recommendations can affect the effectiveness of recommender systems. Most researchers agreed that consumers generally prefer more variety when given a choice (Baumol & Ide, 1956; Kahn & Lehmann, 1991). McGinty and Smyth (2003) empirically demonstrated that there may be significant gains from introducing into the recommendation process. Simonson (2005) proposed that the purchase type and degree of variety-seeking affect customers' acceptance of recommended "customized" offers; in particular, higher rates of variety-seeking decrease a consumer's receptivity to customized offers. In addition, several researchers (Broniarczyk, Hoyer, & McAlister, 1998; Dreze, Hoch, & Purk, 1994; Herpen & Pieters, 2002; Hoch, Bradlow, & Wansink, 1999) showed that consumers' perception of variety can be influenced not only by the number of distinct products offered but by other features (such as the repetition frequency, organization of the display, and attribute differences). Cooke, Sujan, Sujan, and Weitz (2002) studied how customers respond to recommendations of unfamiliar products. Their analysis demonstrated that unfamiliar recommendations lowered users' evaluations but additional recommendations of familiar products serve as a context within which unfamiliar recommendations are evaluated. Further, additional information about a new product can increase the attractiveness of an unfamiliar recommendation. Xiao and Benbasat (2007) also showed that familiar recommendations increase users' trust in the recommender system, and recommender systems should present unfamiliar recommendations in the context of familiar ones. They go on to show that the balance between familiar and unfamiliar (or new) product recommendations influences users' trust in, perceived usefulness of, and satisfaction with recommender systems. Several other researchers (Komiak & Benbasat, 2006; Sinha & Swearingen, 2001; Swearingen & Sinha, 2001) showed that familiar recommendations play an important role in establishing user trust in a recommender system. Further, a user's trust in a recommender system increases when the recommender provides detailed product information. Gershoff, Mukherjee, and Mukhopadhyay (2003) showed that higher of agreement led to greater confidence in a system and a greater likelihood of a user accepting a recommender's advice. Hess, Fuller, and Mathew (2006) showed that a high similarity between users and the recommendations contributed to an increased involvement with the recommendations, which in turn resulted in increased user satisfaction with the recommendations. The similarity in attribute weighting between users and a recommender system has a significant impact on users' perceptions of the utility of the recommendations generated by the system (Aksoy & Bloom, 2001). In addition, (Simonson, 2005) proposed that customers are more likely to accept recommendations to choose a higher-priced, higher-quality option than a lower-quality option and that this tendency is negatively correlated with the level of customer's trust in the marketer. However customer preferences are often constructed rather than revealed, and this practice has important implications with respect to the effectiveness of customizing offers to match individual tastes. This theory is also confirmed by psychological studies (Payne, Bettman, & Johnson, 1993) showing that customers do not exactly know their preferences when confronted with a set of alternatives. On the contrary, preferences are constructed while learning about the choices offered.

In summary, the discussion on recommender systems reveals that (i) most of the body of literature was focused on technical aspects of these engines and on improving their accuracy, and (ii) while the impact of recommendations on customers' behavior is starting to be known, we know very little about how managers should manage these tools and what are the crucial points they should manage when developing a recommender system. Our study's objective is to fill this key gap in the literature. To this end, we proposed 4 critical points, based on an extensive literature and industrial review, consisting of what managers should "do not" when they are going to personalize their website using recommender systems.

The "do not" of personalizing via recommender systems

Considering all the previous literature on recommender systems, we found much work on recommender systems' design and on customers' reactions to recommendations but we did not find significant indications for managers about what they should not do when adopting these systems. In particular, research on how to manage recommender systems is currently underway and it is still quite difficult to define how to do it. However, we can draw several indications from the research on RS about the mistakes that companies should avoid when using RS. Therefore, in this section we present the main "do not" of personalization thus describing the most critical aspects to manage when approaching to use a recommender system.

1. Do not forget about context

Scholars in marketing have maintained that the purchasing process is contingent upon the context in which a transaction takes place. The same customer can adopt different decision strategies and prefer different products or brands depending on the context (Bettman et al., 1998; Lussier & Olshavsky, 1979). According to (Lilien et al., 1992), "consumers vary in their decision-making rules because of the usage situation, the use of the good or service (for family, for gift, for self) and the purchase situation (catalog sale, in-store shelf selection, and sales person aided purchase)". Starting from these studies, several scholars have largely demonstrated how it is possible to include contextual variable in several task (Faraone, Gorgoglione, Palmisano, & Panniello, 2012; Lombardi, Gorgoglione, & Panniello, 2013). In particular, it was broadly how to build contextual recommender systems (i.e., recommender systems which deliver contextual recommendations) using several approaches and it was also demonstrated their dominance on traditional un-contextual recommender systems (Oku, Nakajima, Miyazaki, & Uemura, 2006; Yu et al., 2006). We found several (Ahn, Kim, & Han, 2006; Anand et al., 2007; Baltrunas & Ricci, 2009; Boutemedjet Ziou, 2008; Cantador & Castells, 2009) demonstrating that contextual recommender systems (CARS) outperform un-contextual ones (or perform slightly similar, at least) while we did not find significant evidences of un-contextual recommender systems outperforming contextual ones. (Panniello & Gorgoglione, 2012) also demonstrated that a CARS can generate an accuracy gain which ranges from 20% to 90% when compared with an un-contextual approach. In particular, Table 1 shows the average accuracy gain (among all the settings used in our experiments) when comparing an un-contextual model with four different CARS approaches.

Table 1. Average accuracy gains across RS (RS on the row vs. RS on the column) (Panniello & Gorgoglione, 2012)

There is also a long list of industrial applications that usually adopt contextual recommendations, such as LinkedIn, EchoNest, Telefonica and Netflix. In fact, Hastings, the CEO of Netflix, pointed out recently, Netflix can improve the performance of its RS up to 3% when taking into account such contextual information as the time of the day or location in their recommendation algorithms (watch his interview at 44:40 min at www.youtube.com/watch?v=8FJ5DBLSFe4).

	Un-contextual	First CARS	Second CARS	Third CARS	Fourth CARS
Un-contextual	0%	-31%	-46%	16%	-39%
First CARS		0%	-19%	288%	10%
Second CARS			0%	353%	17%
Third CARS				0%	-49%
Fourth CARS					0%

Therefore the first mistake to avoid is not to forget including context in the recommender system's design. Customers' behavior changes when context changes and so should do recommendations.

An important step for a manager when adopting a recommender system is to analyze data and discover whether some contextual variable exists thus measuring that customers' behavior/needs change when context changes. If so, managers should build their RS considering multi-profiles for users, one for each context, in order to identify, recommend and deliver the right item at the right context. If context is not taken into account when generating recommendations, users may receive the wrong recommendations in a specific moment (e.g., receiving recommendations of kid books when looking for work books or receiving horror movie recommendations when looking for cartoon movies for kids) thus reducing customer's satisfaction, purchases and increasing the risk of customer churn.

2. Do not focus only on relevance of recommendations

After the first wave of publications on how to improve recommendations' accuracy, discussed in the literature review section, there were several studies on building RS focused on different performance measures. In particular, comparing recommender systems in terms of diversity is not new, and it has been done in prior research (Adomavicius & Kwon, 2009; Adomavicius & Kwon, 2012; De, Desarkar, Ganguly, Mitra, 2012; Hu & Pu, 2011; McGinty & Smyth, 2003; Zhang & Hurley, 2008; McNee, Konstan, & Lausen, 2005). Typical approaches would replace items in the derived recommendation lists to minimize similarity between all items or remove "obvious" items from the list of recommendations, as was done in (Billsus & Pazzani, 2000). Several researchers (Adomavicius & Kwon, 2009; Adomavicius & Kwon, 2012) present the concept of aggregated diversity as the ability of a system to recommend across all users as many different items as possible over the whole population while keeping accuracy loss to a minimum, which is achieved by a controlled promotion of less popular items towards the top of the recommendation Furthermore, a trade-off between accuracy and diversity was established in (Adomavicius & Kwon, 2009) and further confirmed in (Gorgoglione, Panniello, & Tuzhilin, 2011), where it was shown that ranking recommendations according to the predicted rating values provides good predictive accuracy but it tends to perform with respect to recommendation diversity. Moreover, Hu and Pu (2011) investigated design issues that can enhance users' perception of recommendation diversity and improve users' satisfaction.

In a recent work (Gorgoglione et al., 2011), several recommender systems were compared using a live experiment and participants were provided with a survey in which it was asked to evaluate the engines on several aspects. Among other conclusions, it was observed that the "random" recommender system (i.e., recommender system that generates random recommendations) reached the highest level of customers' trust in the system. In particular, users receiving random recommendations (i.e., recommendations with high level of diversity but low level of accuracy) rated the question "I trust the system" with a mean value of 3,472 (in a 1 to rating scale) while users receiving content-based recommendations (i.e., recommendations with high level of accuracy but low level of diversity) trusted the system with an average rating of 3,020 (the difference was statistically significant at $p<0,05$). This empirical evidence shows that customers' trust does not depend only on the recommender system's accuracy. If a company aims at increasing customers' trust and improving the relationship with its customers, it has to build a recommender that increase both recommendations' diversity and accuracy (instead of improving accuracy).

Therefore, the second mistake to avoid is not to focus only on relevance. Increasing recommendations' diversity can be as important as increasing recommendations' relevance.

The recommender system should be built focusing on reaching several goals and it has not to be focused only on improving recommendations' relevance. The most important additional goal is to differentiate the list of recommended items thus improving several business (e.g., selling the tails) and customers (e.g., trust or satisfaction) related performance. If the recommender system is built focusing only on recommendations' accuracy, users may get bored of receiving recommendations too similar with their tastes thus reducing their interest in looking at the recommended items list. In addition, not focusing on metrics such as recommendations' diversity may reduce other performances, such as customers' trust.

3. Do not fail in aligning business goal with the customers' value

As shown in literature review section, recommender systems offer the opportunity to reach several different goals in terms of value offered to customers. In fact, RS can be used to retrieve useful items or information (Herlocker et al., 2004), push customers buy (Fleder & Hosanagar, 2009), improve customers' trust on firm (Pavlou, 2003), increase customers' satisfaction or decision quality (Bharati & Chaudhury, 2004). In previous sections we discussed how context and diversity are important to design a around customers' needs. As an alternative to customer-centric design, it exists a long list of recommender systems designed with a business-centric focus (i.e., a recommender system which has the "business" as its main goal). The problem with type of recommender systems is to align the business goal with the customers' value. One specific customer may be looking for a gift (this is the context) diverse with to his typical purchases (the customer is looking for diverse recommendations). That specific user may be just looking for information on the whole item database and the business goal with that customer should be to make him satisfied thus giving him information of all the items, included the unavailable ones, instead of pushing him to buy. Several studies proposed recommender systems' design, which try to align business and customer perspectives. For example, (Hosanagar et al., 2008) proposed a RS that try to align the business aim of increasing revenue from sales with the customer's value of trusting the recommender system.

The third mistake to avoid is not to fail in aligning business goal with customers' value. Each customer is looking for a specific value from the recommender system.

Managers should mind what customers' value is, such as understanding what they are looking for when using RS or what the customer's role is in the purchasing process (some visit your web site to give suggestions to friends, others do to get information), and align their business goal with the value customers are seeking. Only in this way they can improve revenue, make customers happier (relationship) or make purchasing process easier.

4. Do not personalize always the same way

Recommender systems, as any technological artifact, can be characterized by a life-cycle. When a RS is introduced in a business application for the first time, the on the customers and on the whole business, in terms of adoption and ability to the customer behavior, is limited because of resistance to change, low trust, limited amount of information usable to generate recommendations, low accuracy in customer behavior prediction, and flaws in the technology. In the next phase, the number of grows, flaws are fixed, more information is available and recommendations become more accurate. In the maturity phase, when customers trust the RS, the RS can be improved by introducing new algorithms and options for both keeping the customers' adoption high and differentiating the system from those of competitors. Finally, a RS can decline because the evolution of technology, products and customers habits makes it obsolete. The evolution of the RS life cycle changes several customers' parameters, such as their trust and willingness to interact, because customers become used to the system and can touch the benefits coming from its use. Moreover, the benefit/cost of using more complex recommender systems increases with the RS life-cycle. In as products can become popular, customers can increase their purchase frequencies or rate more products. As a consequence, a bigger quantity of data of increasingly higher quality becomes available to the company which can deploy more sophisticated recommendation strategies (e.g., contextual recommender systems). As the accuracy these strategies increase, the benefits can overtake the costs. Therefore, managers are called to change their recommendation strategies continuously depending on the specific settings in which the firm is. This aspect was recently pointed out by & Riedl, 2012) which explicitly state that user experiences, needs, and interests over the use of RS. (Konstan & Riedl, 2012) also state that RS must be designed to understand the needs of the users at these different stages, and to serve them appropriately.

The decision of what algorithm to adopt is not just a choice between alternative information systems pertaining to the company's operational level to be made only based on the data structure and computational performance. It has a strategic value because it is an important part of the customer relationship management policies of a company. Choosing a certain RS entails defining what recommendations will be delivered to customers, when and how they will presented to them. This can strongly affect the relationship between a customer and the company and determine the way customers perceive the company with respect to the competitors. Choosing the wrong way to generate and deliver recommendations does not require just the redesign of the Web site, it can require to rebuild the relationships with customer and even the entire brand strategic positioning. Figure 1 shows the cycle of a typical recommendation process which starts from identifying the contexts in which customer is, then the RS is built by considering to improve several performance metrics (i.e., diversity) and aligning customer’s value with firm’s goal. All these steps have to be re-defined for each recommendation task since they can vary each time.

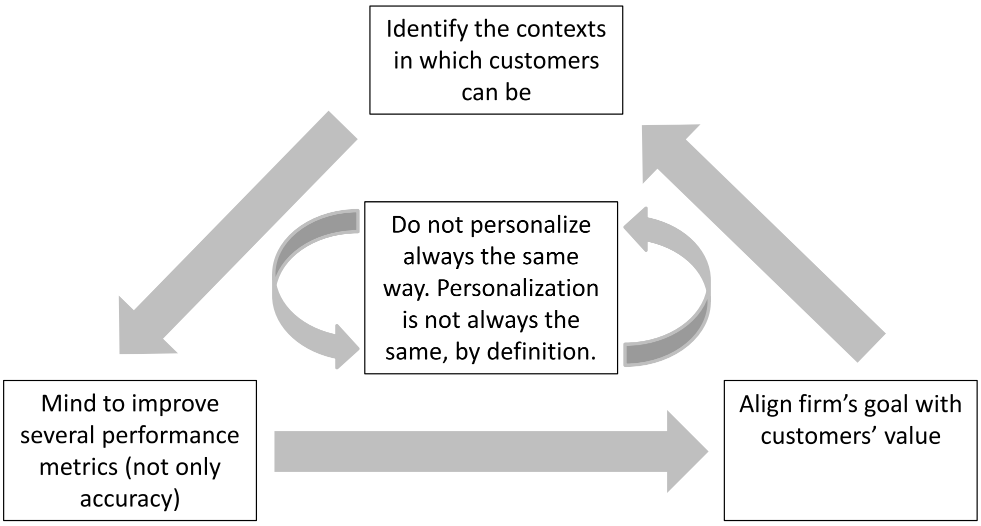

Figure 1. The cycle of a recommendation process

Therefore the fourth mistake to avoid is not to personalize always the same way. As customers and firm evolve, recommendation strategies have to evolve and be modified over time. Managers should mind that they have to personalize the recommendation process as a whole and they do not have to personalize only the list of recommended items to customers. They have to personalize communication, channel used to deliver recommendations, context, focus of the engine for each specific user over time. In other words, they have to personalize the recommendation strategy with each user instead of simply personalize the recommendation list of items.

Conclusions

Recommender systems were developed as tools to solve the information retrieval problem for users searching on large database. These systems create users profile using past purchases, transactions or ratings, and find the items that matching the most with these profiles. However, after the first works on recommender systems, they have quickly become very popular among businesses as online marketing tools. This shift in the use of RS from tools for retrieval problem to marketing tools was followed by a shift of the academic works in this field. In fact, most of the papers written in this area shifted from studying technical aspects of these tools and on identifying new ways to make them more precise to studying the effects of RS on customers.

Despite much work on these two main streams, we know little about how to manage RS. Therefore we focused the aim of this paper on conducting an extensive literature and industrial review and on identifying some crucial points that managers should mind when developing a RS in order to make it as effective as possible in real world applications. In particular, we found evidences from prior research and industrial applications that lead to the following four mistakes that managers should avoid when managing a recommender system. First of all, it is crucial to identify the contexts in which customers can be and to integrate these contextual variables in the recommender system. Several academic works and industrial applications demonstrated that contextual recommender systems outperform traditional ones and that the use of these systems improves both customer and business related performance. The second point is to build the recommender system improving several different performance metrics, instead of the sole recommendations' accuracy. In fact, it was broadly demonstrated that building a recommender system which improves other performance metrics, such as recommendations' diversity, leads to better industrial results. The third critical step is to align the customer perspective with the business one. When developing a recommender system, managers should consider the opportunity of deploying a business-centric designed RS in their firm. However, they should mind to combine the business goal with the customers' value thus making the RS effective for both the parts. The fourth crucial aspect is to continuously monitoring and modifying the recommendation process depending on the RS's life cycle. In fact, it is necessary to modify the recommendation strategy over time and for each customer since personalization is not always the same, by definition.

This work constitutes the first step towards an ambitious goal of understanding the business implications that need to be discussed when adopting a recommender system and defining the guidelines on how to manage these systems. Therefore, much more work is required in order to achieve this goal. For example, as a future work, it would be interesting to study whether other critical aspects do exist when managing a recommender system. Finally, it would also be interesting to identify the factors that make necessary to change the recommendation process over time.

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