A Personalized Recommender System for SuperValu

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Abstract. In this paper, a personalized recommender system is proposed for the online store of SuperValu which currently lacks one. The front-end design of the website has a lot of white spaces and a recommendation widget can be easily accommodated on every web page. The content of the recommendation widget would change in accordance with the web page being currently viewed. To achieve this functionality and tackle the humongous amount and variety of products found in such an online grocery store, a combination of data mining techniques, content-based, collaborative-filtering and knowledge-based recommendation approaches have been used to. To set the online SuperValu store apart from other competitors, a component that suggests recipes to consumers is built into the recommender system as well.

1 Introduction

Recommender systems have witnessed a massive growth in their popularity in the e-commerce industry owing to the ever increasing and pervasive use of Internet. Over the past several years, different businesses have adopted recommender systems with varying approaches that suit their context to enhance customer experience. GroupLens [1] helps users find their preferred articles in Usenet, Ringo [2] gives music recommendation, Fab [3] recommends other web pages, Levis makes suggestions on articles of Levi's clothing and Reel.com gives movie recommendations.

Grocery shopping, often considered a tedious task has moved many brick-and-mortar stores to setup online shopping websites. SuperValu -

Ireland's largest grocery retailer has followed this trend as well and setup an online shop at supervalu.ie. However, using the website once to make a purchase makes one realize the painful absence of a recommendation system.

In this paper, a recommender system is proposed that can not only enhance the customer journey on the website but also increase shopper penetration, average order value and subsequently overall revenue for SuperValu. Helping customers find products easily will increase the loyalty of the customers, which is very important since the competition is just one click away.

Most recommender systems target a particular type of product like movies, books etc. However, the proposed recommender system is to be implemented for the entire online grocery store dealing with the huge and immense variety of products. To be able to make relevant and accurate suggestions in all contexts a switching hybrid recommender system is proposed which uses a combination of data mining techniques like clustering and association rules algorithm along with content-based, collaborative-filtering and knowledge-based recommendation approach. Clustering addresses the grey sheep problem in Collaborative filtering whereas, using a personalized score (Relative Spend) along with content-based approach addresses the issue of price variation across the various products. The knowledge-based recommendation approach will enable suggestion of not mere products but entire recipes too which has not been achieved by any recommender system yet in the online business of consumer packaged goods.

2 Background Research

This section gives a background of the different recommendation approaches.

2.1 Non Personalized

The most basic recommender systems use the non-personalized approach. The preferences of the users are not taken into account and identical recommendations are presented to each user. These recommendations are in some contexts manually decided by the online retailer or in others by an algorithm that determines the top-N popular items [4]. Non-personalized recommender systems commonly use two types of algorithms: Aggregated opinion and Basic product association recommender [5]. Aggregated opinion approach uses an aggregation function like arithmetic mean [6] on all the customer ratings for a product X .Examples of these include Reddit and HackerNews [7]. Product Association is used by many websites to provide recommendations of the form "people who bought item1 also bought item2" feature. The list of things in 'item2' is determined by mining association rules between items currently present in the user's cart and the other items in the catalog. Apriori [8] is the most widely approach used for frequent item set mining

Pros & Cons

Non-personalized recommender systems can be implemented almost effortlessly because of their nature of only requiring the most popular items [9]. The input data to this recommender system is easily available as well [4]. However, as the recommendations lack personalization, they are not going to be favorable to all the users. Also these systems face the banana trap problem in clustered diverse population [9] [10].

2.2 Content-Based

Content-based recommendation systems try to recommend items that are similar to those a given user has liked in the past [11]. It operates under the assumption that items with similar features will be rated similarly [4] These systems typically have a mode for describing the items that may be recommended, a way for building a user profile with the types of items he likes and finally an algorithm for comparing items to the user profile to determine what to recommend [12]. The items in the inventory that are most similar to a query or user's profile are then recommended [3]. The feature space of the item is built using information retrieval techniques.

Pros & Cons

In many cases item features might not be available in which case they will have to be authored manually which is quite tedious and impractical [4]. Content-based recommendation systems fail to give good recommendations if the content does not hold sufficient information to differentiate items that will be liked and dislike by the user. For e.g. it would be possible to tell a painter joke from a sport joke based upon word frequencies, but it would be difficult to differentiate amongst all sport jokes in the absence of item features [12]. Billsus and Pazzani [13] have shown that any machine learning algorithm may be used as the basis for transforming user ratings to attributes. The technique also suffers from the cold start problem and the stability vs. plasticity problem [4].

2.3 Collaborative - Filtering

Collaborative filtering algorithms use past user's behavior and other users' opinions [14] to determine items that might be of interest to the user [5]. Collaborative filtering consists of three primary tasks – representation, neighborhood formation and recommendation generation [15]. Breese et al. [16] categorizes CF algorithms into two classes: memory-based algorithms that require all ratings, items, and users to be stored in memory and model-based algorithms that intermittently create a synopsis of ratings patterns offline.

Pros & Cons

Collaborative filtering systems are independent of the domain they are applied in and are extremely popular because of their ability to make serendipitous recommendations as they look outside the target user's profile [17] but they suffer from a ramp-up problem [9] which is a two-part problem. The system isn't very accurate if it contains only a small base of ratings, hence it needs a large amount of data. Additionally, its accuracy is very sensitive to the number of rated items that can be associated with a given user [2]. When a new item is added to the catalog, it has very low probability of being recommended until enough users have rated it [3].

2.4 Demographic – Based Recommender System

Demographic based recommender systems use demographic information to create association rules of liking between a type of user and a certain types of item [18]. LifeStyle Finder is an example which places the consumer into one of the 62 pre-existing clusters [19].

Pros & Cons

As user/item ratings are not required, even new users can get recommendations or new items can be recommended [4]. This recommender system is domain independent too as it needs only demographic information. However, it's not easy to gather demographic data [18] and leads to privacy issues as well [20]. The association rules and the following recommendations generated by demographic recommender systems might not always be stable [21] and suffer from the grey sheep problem [22] as well as stability vs. plasticity [23] problem where users' tastes change over time.

2.5 Knowledge-Based Recommender System

This type of recommender system uses the knowledge it has about the users and products at hand to employ a knowledge-based approach to determine which products effectively accommodate the users' requirements and makes recommendations accordingly [9]. A case-based recommendation approach, also considered to be a type of content-based recommender system is the most popular approach amongst knowledge-based recommender systems.

Pros & Cons

A knowledge-based recommender system doesn't suffer from ramp-up problem as it is independent of user ratings. It doesn't have to gather demographic information or build user profiles as the recommendations are independent of individual tastes [9].

2.6 Opinion Mining - Based Recommender System

Most websites allow users to write reviews for items in addition to giving ratings, wherein users explain the reason behind their rating. This approach uses the information within this review [24]. 'Ratings with Reviews' [25] is an example of a recommender system that uses the opinion-mining approach. It maps every latent feature with a word cloud which explains the meaning of the feature. The 'Hidden Factors as Topics' [26] is another example which can discover highly interpretable product features that are good candidates to explain the variation in the ratings by different users.

Pros & Cons

This approach helps to alleviate cold-start problem when the ratings data is sparse [25] and make recommendations only with a few reviews.

2.7 Hybrid Recommender System

As the name implies hybrid recommender systems combine two or more recommendation approaches in order to gain better performance and accuracy as an ensemble. The limitations of the individual approaches are overcome as an ensemble. There are multiple ways called hybridization methods by which recommendation approaches can be combined [28]. For e.g. in weighting, the scores/votes of the different techniques are combined together or in switching, the system switches approaches depending on the situation. The most popular combination for hybrid recommender systems is a combination of content-based and collaborative filtering, with the most earliest one being in 1999- Fab[3] for recommending web pages to the most recent in 2017 – A restaurant recommendation system[27].

3 Design

SuperValu is Ireland's biggest grocery retailer [28]. In addition to its 223 brick and mortar stores, it allows its customers to shop online at its website supervalu.ie as well. SuperValu recorded retail sales of €2.67 billion in 2016 of which online shopping was a key sales driver having grown by 22% in 2016 [29]. So it's worth the organization's time and effort to increase the conversion rate of its online store.

In its current state, the SuperValu online store is rather alike to an online catalog, wherein it merely displays all the products it stores broken down by categories and the offers that the store owner wants to promote. The consumer has to browse categories and sub-categories to reach to the product they are looking for and subsequently add only that specific product to the cart. This makes for a tedious shopping experience for the consumer.

Most physical stores use some product association algorithms to determine the store layout, so as to tempt consumers into buying products they did not plan to buy. Compared to this, the SuperValu online store feels like a "dead" space as there are no such suggestions.

A recommender system is proposed in this paper that helps address these problems and bring additional advantages to the business as well. A personalized recommender system will enhance the shopping experience, in particular the browsing part of it for the consumers, thus mitigating the risk of losing out on customers to other competitors because of poor design. It's a strategic advantage for SuperValu as well as it encourages a consumer to buy products he initially had not planned to. Furthermore, as the usage of the recommender system by the consumers increases, the quality of the recommendations it produces will elevate as well.

The proposed SuperValu recommender system is designed using a combination of two data mining techniques –clustering and association rules algorithm along with content-based, collaborative-filtering, and knowledge-based recommendation approaches. This recommender system will interact with the consumers at various points during their shopping experience, but can be classified into 'Check Out' and 'In Store' recommendation [30].

3.1 In-Store Recommendation

This includes the various points of recommendation whilst the consumer is browsing the products he is looking to purchase.

3.1.1 All Categories Page

A user lands on this page immediately after login. Currently, it displays all the product categories at the top of the page with a search bar at the top right of the page. This is the point of entry for the consumer's shopping experience. He is overwhelmed with the variety of options available to him and isn't sure of where to start. There is a split-second opportunity here to provide crucial personalized recommendations at this stage to either prevent the customer from dropping out of the session or to entice him to make unplanned purchases. In the proposed recommender system, the user would see recommendations about products to buy at the top of the web page. These recommendations

Figure 1: All Categories Page

would be a mixture of products, the user frequently purchased in the past and those determined by the recommender system for the current user.

3.1.2 Category Page

This is the page the consumer lands on when he clicks on one of the categories like 'Fruit & Vegetables' or 'Dairy'. Currently, this page shows additional sub-categories and top offers within this category at the top of the web page. It's essentially similar to the 'All Categories' page but at 'level 2' of the user browsing experience. It's essential that the recommender system doesn't confuse the user by exhibiting different modalities of recommendation for similar content.

Figure 2: Category page

Consequently, a similar recommendation design is proposed for the 'Category' page as the 'All Categories' page. However, it's different with respect to the products displayed in the recommendation row, as these will belong only to the category being looked at currently.

3.1.3 Product Page

This is the page the customer lands on after he clicks on a particular product like 'Milk', 'Bread', 'Banana' etc. Currently the page displays a picture of the product along with text giving a short description of the product being looked at. It is proposed to add a row[1] right below the product picture and above the text that displays recommended products determined from clustering and association rules algorithm. SuperValu online store also hosts a recipe section where one can find detailed recipes for delicious meals. This database can be exploited to increase the recommender system's effectiveness and relevance.

Directly below the row of recommended products[2], recipe suggestions would be made that can be prepared using the product currently being looked at and the products in the user's cart currently if any. The user could add the entire recipe to their cart, which would prompt all the constituent ingredients to get added to the cart. Lastly, in the same row, at the rightmost end[3], recommendation would be made about a premium version of the current product. It would be the same product for a different brand that has a higher quality/price, something which the store is interested in upselling.

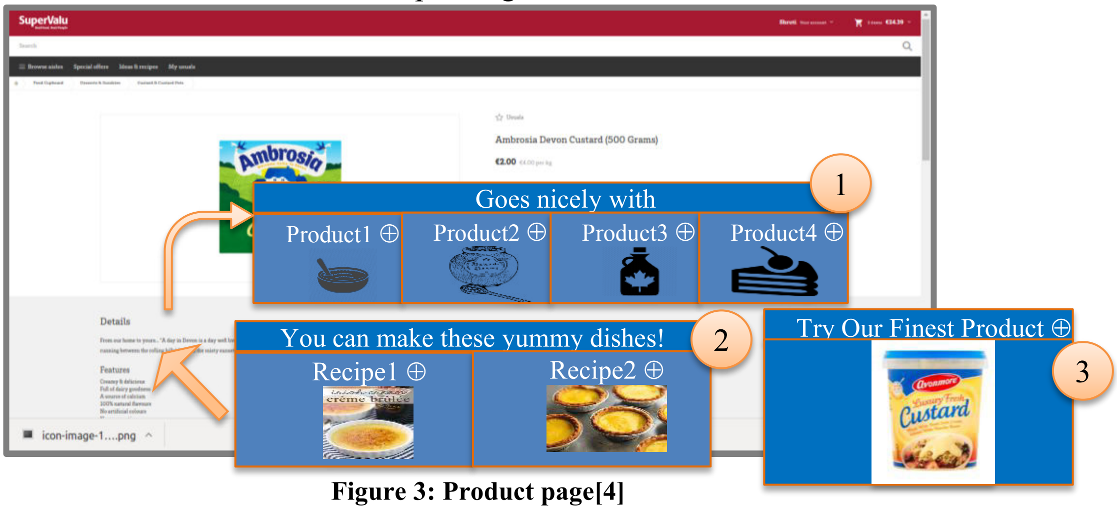

Figure 3: Product page[4]

A consumer can also add a product to his cart directly from the category pages. In such a scenario, a small popup at the bottom left of the screen would display the most promising recommendation for the current user in relation to the item that just got added to the cart.

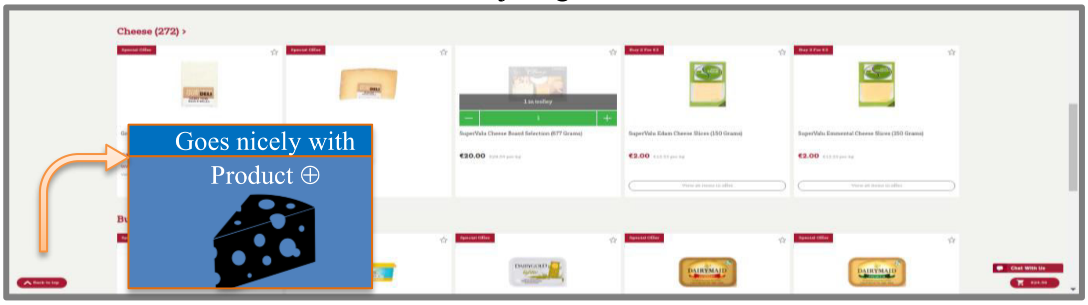

Figure 4: Product Addition from Category Page

3.2 Checkout Recommendation

This recommendation is provided to the user at the end of his shopping journey, at the checkout page. Currently the 'Checkout' page is void of any suggestions and consists of only forms pertaining to payment methods, contact information etc. The checkout page- being the point of exit of the shopping experience is as crucial as the point of entry. There are opportunities to upsell and cross-sell products here. As has become the norm in many e-commerce websites, it's proposed to add a table of recommendations at the right hand side of the page.

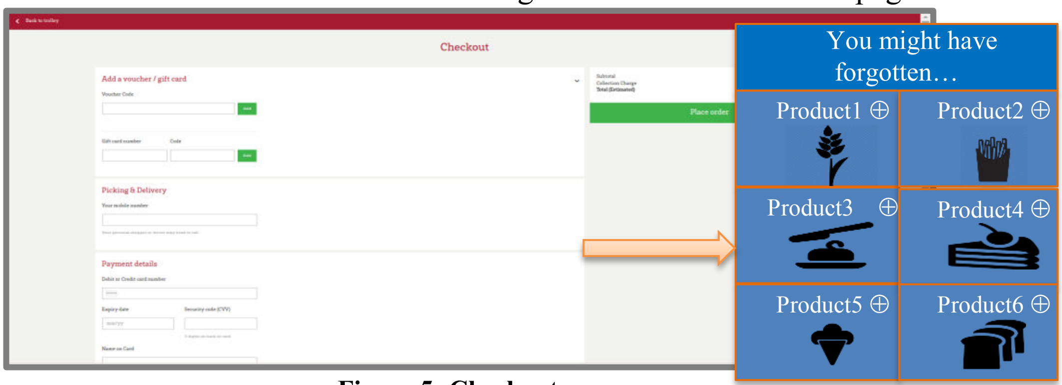

Figure 5: Checkout page

These recommendations would contain a mix of products that were present in the user's previous transactions, but missing in the current one and products deemed recommendation worthy by the recommender system [30].

4 Algorithms

4.1 Data Sources

Items - The products available to purchase on the online SuperValu store are modeled as items in the recommender system. Each product/item is described by features like name, product category, product sub-category, product price, product description. All this information is stored by SuperValu for their online store.

Users - The SuperValu online store requires a customer to register with the website, before it can place an order. Therefore, the recommender system has access to user data as well and information about the user such as his contact information, payment method and location.

Transactions - Every order placed by a customer can be termed as a single transaction. From the presence of the 'My Orders' tab post login, it can be inferred that SuperValu stores information about each transaction and the recommender system will have access to transactional details like the products involved in the transaction, their

quantities and the overall transaction price. Number of transactions here are the equivalent of ratings.
Recipe - These are considered as items by the knowledge-based recommender system for the Product Page.

4.2 Data Modeling

Users-Products - This data can be modelled in the form of a matrix, where the users act as the columns and the products act as the rows. Each cell in the matrix gives the recommendation score for a particular item for a particular user.
Recipe - This data can be modeled as a matrix where all the culinary products form the columns of the matrix and each recipe appears in a row of its own. If a particular product is part of a recipe, the corresponding cell contains the value 1 else 0.

4.3 Recommender System Algorithm

The proposed recommender system is a switching hybrid recommender composed of data mining techniques like clustering, product-association rules, content-based, collaborative filtering and knowledge-based recommendation approach [31]. A switching hybrid is used as there are multiple opportunities of recommendation on the SuperValu online store and different techniques are suitable for different contexts.

4.3.1 Category Pages & Checkout Page Recommender

This system consists of three main parts: - clustering the customers, generating product association rules for each cluster and using this information to generate a recommendation score for a particular product for a specific user.

Customer Segmentation - This step uses the data mining technique of clustering to segregate customers into different groups such that customers within the same group have similar purchase behaviour. The choice of the clustering algorithm – partitional or hierarchical will be decide through experimentation to see which algorithm gives more defined clusters [31].

Content-Based Recommendation - To characterize customers a personalized factor called Relative Spend (RS) (< 1) is used, which is an assessment of customer expenditure at product level. It determines the significance of the purchase of a product involved in a transaction with respect to the overall sales of that product. For example, consider that a customer X buys four products A_1, A_2, B_1, B_2 and C_1 for 30, 20, 30, 10, 10 dollars. Here total transaction amount is 100 dollars; A_1, A_2 belong to the same category and so does B_1 and B_2. The RS of customer X with respect to the products A_1, A_2, B_1, B_2 and C_1 is 0.3, 0.2, 0.3, 0.1 and 0.1 respectively. If the data is viewed at product category level, the RS of customer X with respect to product categories A, B, and C is 0.5, 0.4 and 0.1 respectively. These RS scores are subsequently divided by the average RS scores for each product across all transactions to get the Normalized Relative Spend (NRS) factor. For e.g. if category A had an average RS score of 0.1, then the NRS for customer X and category A would be 5.0. The content-based method is used to set an initial score for each product which is the average NRS value of all the products in the cluster. The average NRS score for a product type is directly proportional to the probability of the users in that cluster purchasing that product type and hence acts as a good recommender score [31].

Association Rules and Collaborative Filtering - After setting the initial recommender scores, the association rules algorithm is applied on each cluster to determine rules in the form of X →Y. These rules are used to manipulate the recommender scores for products that appear on the right hand side of the rule (Y in this case) by the given formula (Eq. 1) where c is the customer ID; NRS(Y) is the NRS for product Y from customer c's cluster. |P| is the number of previous transactions including product P. Confidence[X →Y] is the confidence value for the association rule X →Y for the cluster currently being looked at. If |Y| > 0, it means that the customer has already purchased product Y and hence should not be recommended Y, hence the recommender score for

$$Recommender\ Score(c, Y) = \begin{cases} 0, \ |Y| > 0 \\ max\big(Score(c,Y), NRS(Y)\big), \quad |Y| = 0 \wedge |X| = 0 \\ max\left(Score(c,Y), NRS(Y) * \dfrac{Confidence[X \to Y]}{1 - Confidence[X \to Y]}\right); |Y| = 0 \wedge |X| > 0 \end{cases}$$

Equation 1: Recommender Score calculation

product Y is set to 0. When both |X| and |Y| is 0, i.e. the customer has not purchased either X or Y, then the customer c is assumed to follow the purchase behaviour of the cluster he belongs to and hence the recommender score is set to the maximum value between NRS(Y) and Score(c,Y) of the cluster under examination. In the remaining case, where user has purchased X previously, but not Y yet, i.e. |X| > 0 and |Y| = 0, the recommender score for product X is the higher value between Score(c,Y) and NRS(Y) * Confidence[X -> Y]/ 1 – Confidence[X -> Y] for the current cluster [31]. The products with the highest recommender scores for customer ‘c’ are presented to him as recommendations on the category pages and the checkout pages.

The suggestions shown on the checkout recommender page is a blend of products with the highest recommendation scores determined using the above procedure and the ones frequently occurring [30] in the customer’s previous transactions but missing from the current transaction. The products with the highest count value are shown in the recommendation box.

Algorithm: Most Frequent Products for customer C

$T = T_1, T_2, \ldots T_n$ $previous\ transactions\ by\ customer\ C$
$P_{all} = T_1 \cup T_2 \cup \ldots T_n$
$P_{current} = Products\ in\ current\ transaction\ T_c$
$P_{missing} = P_{all} - P_{current}$
$FOR\ each\ product\ P_i \in P_{missing}$
    $P_i.count = 0$
    $FOR\ each\ transaction\ T_j \in T$
        $IF\ P_i \in T_j$
            $P_i.count++$
        $END\ IF$
    $.END\ FOR$
$END\ FOR$

4.3.2 Product Page Recommendation

‘Goes Nicely With’ - Recommendations for this section are generated using a combination of clustering and product association rules discussed in the previous section. At first, the cluster to which the customer belongs to is determined. The product-association rules for this cluster are retrieved. If the customer is looking at product P, then all the association rules of the type $P \rightarrow A_1$, $P \rightarrow A_2$ … $P \rightarrow A_n$ are filtered where P is the base product. This list is sorted by their corresponding Confidence [P $\rightarrow$ A_i] values and the top 6 (customizable) are displayed as recommendations to the customer.

Recipe suggestions - This section utilizes a query-based approach from the paradigm of knowledge-based recommender systems. The system stores a list of recipes and their required ingredients and is therefore knowledgeable about which recipes can be concocted using the product being looked at currently or a combination of the products in the user's cart. The query sent to the recommender system consists of a list of features (ingredients) which is a union of the products in the user's cart and the product page he's looking at currently. For e.g. if the user's cart contains of the products milk, sugar, eggs, butter and the user is looking at the product page of 'vanilla essence' currently, then

$$Query(Q) = milk \,\&\, sugar \,\&\, eggs \,\&\, butter \,\&\, vanilla\_essence$$

Conceptually, each recipe is represented as a tuple <I, N, F> where I is the unique recipe identifier, N is the name of the recipe, and F is the feature set of all possible ingredients. The feature value is set to 1 or 0 indicating presence or absence of the feature (ingredient). The system computes a relevance score with respect to the query for each Recipe R in its database.

$$Relevance\ Score(Recipe) = \sum_{I \in Q} (Recipe[I] \oplus 1)$$

Recipes with top three (customizable) relevance scores are then showed as suggestions.

Try Our Finest Product - This recommendation is made using case-based recommendation approach. The objective is to retrieve a 'case' - a product in this context, most similar to the product being looked at currently, but with a tweak [32] of being more expensive operating under the assumption that product quality is directly proportional to product price. The recommender steps follows 3 basic steps: retrieval using similarity, elimination to accommodate the tweak and sorting by number of transactions. Conceptually, a product p is represented in the system as a tuple <I, N, F> where I is the product id, N contains the product name and F is the set of features of the product [32]. The input to this system is the product id of the current product. It looks up the feature set F of the current product and retrieves T – the set of all products with feature values similar to those in F. All the products that don't satisfy the tweak (higher price) are eliminated from T. Subsequently, T is sorted in a descending manner based on the number of transactions a product was involved in. The top product in T is then recommended to the consumer as the 'Finest Product'.

5 Conclusion

Recommender systems are a powerful tool for tackling the information overload problem and establishing personalization. An effective recommender system can benefit both consumers and businesses by making serendipitous suggestions to the consumers and increasing sales for the businesses. SuperValu's online sector grew by 22% in 2016, and it is in its best interest to deploy a recommender system on their site.

There are several types of recommendation approaches, some more suitable than others in a particular situation. Collaborative recommenders help in harnessing the power of 'similar users, similar tastes' but don't do a good job for users with unusual tastes. Knowledge-based recommenders use their overall knowledge about the domain and data to make suggestions to the consumers. Hybrid recommender systems allow the choice of an approach most appropriate to the context and also overcome the shortcomings of the individual approaches. However, a recommender system isn't capable of directly working with the data that is collected. Appropriate data mining techniques are required to filter and assimilate information, on which suitable recommendation generation techniques can be applied.

The knowledge-based recommendation component responsible for recipe suggestions is a salient feature of this recommender system. However, currently it gives suggestions only looking at the current cart of the user. A temporal context can be added such that it keeps tracks of the user's purchased ingredients and makes suggestions incorporating this information as well. Moreover, the association rules algorithm can be enhanced to use sequential pattern analysis as well. This would enable the discovery of time related attributes and analysis on a seasonal basis would be possible. The current system only understands the general purchase behavior. Understanding the purchase behavior on a seasonal basis would lead to more accurate product recommendations.

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