BUSINESS INTELLIGENT RECOMMENDER SYSTEMS

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Abstract- In recent years, we have witnessed the presence and role of recommender systems bringing in new opportunities and challenges to the business world. In this paper, we explore how business intelligence concepts could be applied to recommender systems to enhance their capabilities and responses to complex events. We propose a framework for Business Intelligent Recommender System and illustrate its application in B2C e-commerce as a case example.

Keywords- Recommender Systems, Business Intelligence, Data Analytics, Data Mining, E-Commerce.

I. INTRODUCTION

A recommender system is a software program that aims to recommend personalised items (products or services) to the users and have been developed for a variety of applications [1]. It adopts active and selective information-filtering techniques on the history of user behavior data to suggest meaningful information contextualized in order to achieve the goals of each end-user [2]. Since mid-1990s several recommender systems have been proposed for a variety of applications [3]. Apart from providing with personalized product or service recommendations, they are increasingly required to improve customer relationship management. With such a crucial role in today's context of customer-centric products and services, a recommender system is required to assista user in various forms to locate, discover, and find the item by predictingthe user's interest based on related information about various itemsand even interactions between items and users.

Traditionally, the main purpose of recommendations for e-businesses is for sales, be it to provide information filtering to assist and educate consumers or to build a community of users around products or content [3]. With the ever-changing society and technological advances, there is a need to re-engineer the existing recommender systems adoptingtraditional methods provide recommendations, predominantly text-basedFuture recommender systems are expected toleverage on Big Data and incorporate business intelligent methods that can intelligently caterto diverse user requirements and goals [4]..Recent research has identified the need for recommender systems to hasten analysts'response to complex events such as cyber attacks and tailor the recommendations to the intelligent community [5]. While recommender systems have served common domain such as e-commerce traditionally, futureuses wouldinclude recommendations for dynamically changing and complex situations, such as suggesting traffic routes, predicting careers, etc. in order to provide most suitable information of high value to active users of an e-commerce business system, a customized recommender system is required [6]. Modern e-businesses would like to have intelligent and context-aware information filtering for its active users to find the best suitable goods of their interest with diverse content, such as movies, audios, books, and documents [7].

More recently, with more and more personal informationmade available and processed, there arises a new set of privacy and confidence issues [8]. Users raise various concerns with queries such as "who knows what items about me?", "Is the recommendation correct and trustworthy?", "what is the vulnerability to external manipulation?", etc. A trust-based model is necessary for a business intelligent recommender system. With significant advances in machine learning, artificial intelligence techniques could be employed to include trust-based business rules while miningrelevantuser datafor identifying new and useful patterns [9][10]. These enhancements would provide greater promise to recommender systemsfor embracing business intelligence. Hence, in this paper we propose a framework for such a business intelligent recommender system.

The remainder of this paper is structured as follows. Section II provides a review of the main types of recommender systems highlighting the commonly adopted recommendation techniques with similarity measures. In Section III, we propose a framework for a Business Intelligent Recommender System and describe the salient features of its components and model steps. Section IV presents a case example providing the application of our proposed framework in a B2C e-commerce scenario. Finally, conclusions and future work are given in Section V.

II. A REVIEW OF RECOMMENDER SYSTEMTYPES

Different definitions of a recommender system are available in literature. In general, recommender systems are software agentsthat elicit the interests and preferences of individual consumer to make recommendations while facing choices and options for facilitating decision making. A recommender system

is often present in e-commerce landscape where the website provides recommendations of products and services based on users' opinions that might be of their interest [11]. Questions such as what and howinformation is gathered and processedshould be considered while constructing a recommender system based on its purpose and desired usage. These ramifications lead to the type of recommender system developed. Though there are several different classifications of recommender systems found in literature, the variations are minor and they broadly fall under five main types based on the recommendation techniques they employ, namely collaborative, content-based, demographic, utility-based, and knowledge-based [12].

Irrespective of the type of the recommender system, in general, a recommender system should be capable of finding things that are of interest, helps to explore the space of options, narrows down the set of choices, etc. that are of added value to each user. To the recommender system provider, it offers opportunities for promotion of products and services, obtains useful knowledge about customers, employs techniques for incorporating persuasion, trust and customer loyalty Increase trust and customer loyalty to increase sales, click through rates, and sales conversion [13]. A typical recommender system uses ratings, preferences, demographics, situational context of its consumers and the item characteristics to find relevance score used for rankings to recommend items. However, different types of recommender systems could arrive at different user goals for providing personalized recommendations while reducing the information overload by estimating relevance thatis context-dependent and with diverse characteristics.For example, a collaborative type recommender system would try to satisfy the user's requirement: "Tell me which item is popular among my peers", while a content-based requirement is: "Show me more of the same item that I have liked", or a knowledge-based would be: "List those items that fit within my needs", a utility-based is:"Show me the most usefulitem for me", and a demographic type would be:"Tell me which item is suitable for this location". There are also hybrid types that combines different techniques.

The most widely implemented type of recommender system is the collaborative-type where the "wisdom of the crowd" is usedto recommend items [14]. The system aggregates ratings of items, identifies common patterns between user ratings, and finally generate new recommendations based on inter-user correlations [15]. However, the assumption is that users give ratings to catalog items and that their preferences and likes are similar both in the past as well as the future. Demographic type recommender systems also employ a similar collaborative filtering technique on demographic information collection from the users based on, for instance their location and time of the day, where the data does not rely on historical ratings and preferences of the users [16]. Since both collaborative and demographic types rely on users and not on the content, we describe a similarity measure (*sim*) commonly employed for both types, namely user-based nearest neighbor based on Pearson correlation as given below [17]:

a, b : users

$r_{a,p}$: rating of user a for item *p*

P : set of items, rated both by *a* and *b*

Possible similarity values between -1 and 1;

$\bar{r}_a$ = user's average ratings

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r}_a)^2}\sqrt{\sum_{p \in P}(r_{b,p} - \bar{r}_b)^2}}$$

A popular prediction measure (*pred*) from the neighbor's rating is calculated by:

$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}$$

Since collaborative technique requires some form of rating feedback, it leads to cold start for new users and new items, and the quality of recommendation much depends on large historical user data. Contrary to collaborative and demographic techniques where the focus is on the users, content-based recommender systemsfocus on the items [18]. They defineitems of interest according to their associated features and employ item-to-item correlation. Based on this and the properties of items that users have liked, the system forms users' interest and preferences. Similar to collaborative filtering technique, this technique also requires an extensive use of the system to learn users' interests and preferences. Early stage of interaction with the recommender systemwould lack accuracyof recommendations and the confidence level may be low as the keyword usage may be restricted. A commonly used similarity measure (*sim*) for an unseen item with the user profile based on the keyword overlap is given below [17]:

$$sim(b_i, b_j) = \frac{2 * |keywords(bi) \cap keywords(bj)|}{|keywords(bi)| + |keywords(bj)|}$$

However, such a simple keyword-based measure has its limitation since different words have different importance and longer documents provide a higher chance of overlap with the user profile. Hence, term frequency (*TF*) measures normalized with respect to document size, along with inverse document frequency (*IDF*)to reduce weights of terms appearing in all documents,are used to calculate the overall importance of words (*OverallImp*) as follows:

Given a keyword *i* and a document *j*

$$OverallImp\ (i,j) = TF(i,j) * IDF(i)$$

whereterm frequency (TF) is defined as:

$$TF(i,j)$$

$$= \frac{freq(i,j)}{maxF(i,j)}$$

[*freq(i,j)*: number of occurrences of keyword *i* in document *j*;

maxF(i,j) denotes the highest number of occurrences of another keyword of *j*]
and inverse document frequency (*IDF*) is defined as:

$$IDF(i) = log\frac{N}{n(i)}$$

[*N*: number of all recommendable documents;
n(i): number of documents where keyword *i*appears].

The limitation here is that such keyword importance measures do not capture the semantics nor negative contexts. In addition, due to the diverse formats of content, keywords alone may not be sufficient to determine importance of an item.
One commonality among the abovementioned three recommendationtechniques is their suitability for long-term generalizations about their users that gives them long-term benefitswith prolonged use and interact with the system and as the system gets more familiar with the users' preferences. On the contrary, the remaining two recommender system types, namely utility-based and knowledge-basedprovide recommendations bymeasuring the match between users' needs and the set of options available.

A typical utility-based recommender systemprovides suggestions to a userby computing the utility of an item for the userbased on the user profile. The focus is on the utility than on the users or products, and the approach is to consider various factors such as product stock level or vendor reliability when making recommendations for the users [12]. However, if not designed intelligently, a utility-based recommender system could suggest a relatively more expensive item based on a match with the immediate userrequirement. This drawback is addressed in a knowledge-based recommender systemthat arrives at inferences by employing reasoning about its users' needs and their preferences before making suggestions [19]. It makes use of various domain knowledge such as product and sales knowledge elicitation from domain experts and sales experts, elicitation from users on their requirements in order to guarantee a more reliable recommendation [10]. A typical distance similarity (*similarity*) between the item attribute (*p*) and the user requirement (*r*)is defined below:
sim(p, r):distance of item attribute *p* value to the customer requirement $r \in REQ$.
w_r:importance weight for requirement *r*

$$similarity(p, REQ) = \frac{\sum_{r \in REQ} w_r * sim(p,r)}{\sum_{r \in REQ} w_r}$$

The limitations here are in knowledge acquisition from domain experts, users and the web, which could be time consuming as the accuracy derived through fine granular preference models require many interaction cycles with the user or sufficient detailed data about the user [20]. Hence, knowledge-based recommender systems do not react to short-term trends.
Considering the pros and cons of the abovementioned 5 types of recommender systems, in the next section, we describe the need for a hybrid system in the recent business context of Big Data. We propose a framework for recommender systems to embrace business intelligence to overcome different limitations of the aforementioned five types of recommender systems.

III. PROPOSED FRAMEWORK

Today's dynamic and competitive business scenariorequires recommender systems to be implementedas a combination of two or more types of recommendation techniques. They are called hybrid recommender systems where different techniques are employed according to the given situation [12]. For instance, for a new user, the recommender system may employ various proportion of weight on content-based technique and as the new user provides more information and input to the system, the system progressively learns the habits, interests, and preferences of the users and therefore can start to build confidence in recommending items [16]. In addition to technique combination, further improvement on recommender systems can be achieved through the incorporation of contextual information into the recommendation process, additional support for multiple criteria of ratings, as well as improvement in the understanding of users and items [22].

For the recommender system to be successful, apart from adopting a good similarity and prediction measures, importance should be given to the interaction methods adopted for user persuasion strategy and for educating users about the product domain that would build user trust [21]. Further, businesses would consider the conversion rate as success criteria by keeping track of increase in sales margins and profit that relate touser measures of their online products and services, such as "hit", "clickthrough", "lookers-to-bookers" rates. These are possible by adopting BusinessIntelligence (BI), where the data is stored in data warehouses (DW) and some of the tools that are commonly used for analysis include OnLine Analytical Processing (OLAP) and data mining [9]. The performance monitoring tools of BI could be used to monitor the recommender systems and support decision making. The decision making consists of two kinds of data such as historical data or OnLine Analytical Processing (OLAP) and day-to-day transaction data orOnLine Transactional Processing (OLTP) [4]. Such a business intelligent recommender systemwill be able to answer the question "What was

the company's revenue due to this user recommendation?", the fact table would contain the measure "revenue" and one of the dimension tables would have a "user recommendation" attribute. Fig.1 provides a framework of the proposed business intelligent recommender system.

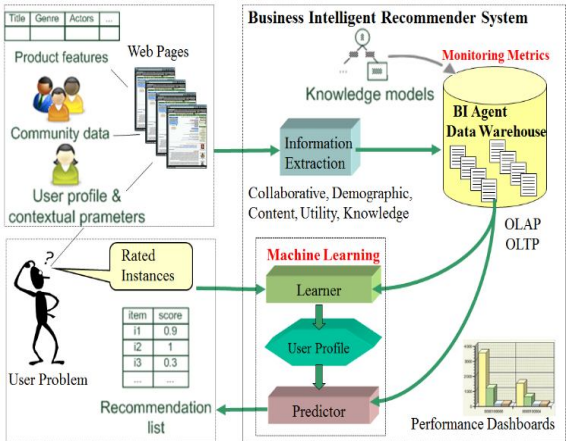

Fig. 1. Proposed business intelligent recommender system

In the proposed business intelligent recommender system, each user problem/query/interaction is processed to provide a recommendation list by following the high level of model steps given below:

1. The system takes in a collection of inputs that could contribute to decision making. The key inputs gained through web pagesare:
   a) Item based inputs, such as product (or service) features, restrictions, and business context [18].
   b) Social engineering based inputs, such as community data, temporal data, location-based data, and peer ratings/feedback [23].
   c) User based inputs, such as user profileand contextual parameters including ratings, preferences, situational context, and specific demographics that relate to ratings or buying propensity/behaviour [6].
2. Information from the above inputs are extracted by the system using a hybrid set of filtering techniques chosen from the five types (collaborative, demographic, content, utility and knowledge based) depending on the situational context. Expert system components that include knowledge models are employed for identifying and filtering datasets in the data warehouse byusing the previously defined expert rules and domain knowledge that are alsodynamically and intelligently updated.
3. The machine learning component of the recommender system performs learning and prediction from the data collected in the data warehouse using OLAP databases andby applying various data mining techniques to cluster items (say using k-means clusteringbased onrelevance, ratings, similarity, and other factors), to find nearest neighbour of active users, and to arrive at aworking dataset that is bestcorrelated.
4. Based on each user's current activities or long-term preferences and combined with OLTP/OLAP features of the data warehouse and machine learning techniques, the recommender system makes more accurate and valuable recommendations.
5. The performance monitoring component of the BI recommender system uses appropriate monitoring metrics thatare calculated by taking inputs from OLAP/OLTP system to generate performance dashboards and a recommended set of reports. In addition, inputs from external data (e.g.,competitive market analysis and seasonal analysis) are also combined to provide valuable feedback on how well the recommender system contributes towards achieving the business goals.

By integrating the recommender system with Business Intelligence methods, process and technologies, the system is able to employ data warehousing and performance monitoring features to obtain more useful knowledge to the active user for better decision making [4]. Theperformance of the recommendation made could be evaluated by measuring the acceptance rate of the recommendations and compare it previous instances [9]. Such monitoring features of BI help the system to understand how well it is contributing the business goals and adapt itself. Also, performance visualization and explanations of the recommendations made to the user contribute to the value-added functionality of recommender systems [20]. For e.g., a measure of users' positive actions (accepted recommendations) that lead to product sales would determine their benefits to the business. Similarly, monitoring users' negative actions (rejected recommendations) helps in achieving a continuous improvement of the recommender system [24]. In the next section, we describe some the features of a business intelligent recommender system.

IV. CASE EXAMPLE

In this section, we describe how our proposed business intelligent recommender system is applied to a B2C e-commerce website since recommender systems are quite popular e-business environment [25]. We illustrate selected features of the recommender system in a typical e-commerce jewelry store, which specializes in customized jewelry making. Key features in the recommender system, such as product comparison, user reviews and forums and performance monitoring reports using BI are described below:

Search and comparison of products–The search facility in e-commerce websites help customers to

narrow down the products based on keywords related to the products and services. For the jewelry website, filtering options, such as price range, gemstone, metal type, occasion, and other context-dependent parameters are used and combined with comparison feature of similar products to facilitate customers in achieving their goals [7]. Fig. 2 shows an example screen shot of an output from the search and comparisonfeature of the website.

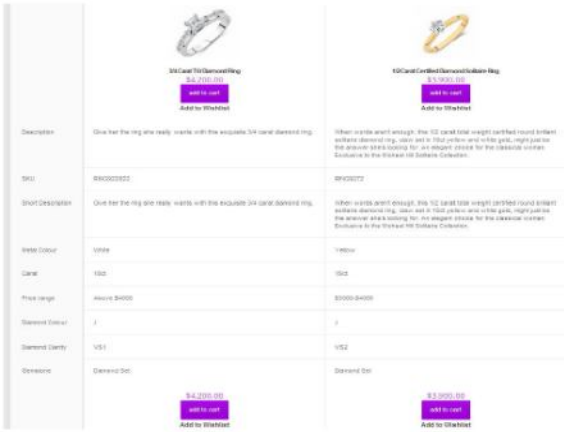

Fig. 2. Context-aware comparison of related products

This context-aware and interactive search combined with comparison of productsempowers customersto effortlesslynavigate pages, to find items of interestquickly, andto take positive actions of the recommendationsforadding the item to their wish list and eventuallyin making informed decisionsto purchase an item.

User reviews, chatsand forums – These features have become a common functionality of e-commerce websites as they help users to get more information about their products in the pre-purchase stage, thereby creating a positive influence on users in making a purchasing decision. Online chats and forums not only increase the level of customer service but also provideadvanced demographic and contextual information about the user and the community data to the recommender system [24]. Fig. 3 shows an example of the user review and online chat/forum functionality of the e-commerce jewelry store.

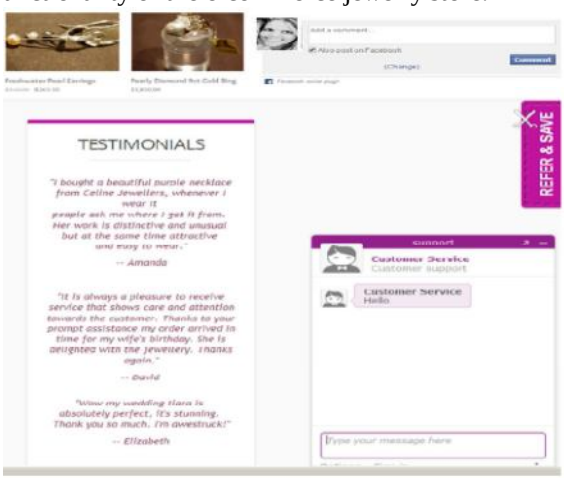

Fig. 3. Social engineering inputs for recommender system

Performancereports/dashboards–Performance monitoring reports such as content efficiency analysis report, keyword analysis report, link analysis report, e-commerce traffic report, etc. are based on continuous monitoring metrics of BI that help in evaluating the recommender systems in relation to achieving the business goals [4]. For e.g., the content efficiency analysis report as shown in Fig. 4 helps to identifythe content that delivers the most business value or the type of content (text, videos, pictures, etc.) that best engages the user.

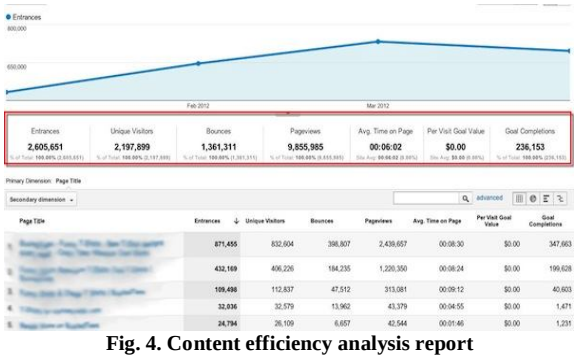

Fig. 4. Content efficiency analysis report

The keyword analysis report considers useful metrics, such as unique visitors, goal completions, goal conversion rate, e-commerce conversion rate, etc. to judge whether they need to make improvements to their campaigns and product promotions and their relationship to revenue [11]. The link analysis and e-commerce traffic reportsprovide information about the websites that are sending the best traffic using metrics such as new versus existing page visits, bounce rate, and per visit revenue [15]. An example e-commerce traffic report for the jewelry website is given in Fig. 5. Similarly, heat map applications that use overlays to show the percentage of visitors clicking a link ormap other traffic sources to userbehavior could beIntegrated in the website in order to see the hotspots on each page.



Fig. 5. Example e-commerce traffic report

With social media playing an important role in consumer behavior, data from social networks related to likes, reach, visits, posts, and people that connect several users can be analysed with various metrics that provide analytics tool, such as Facebook insights [23]. Such a feature of insights dashboards providesocial ranking to connect relevant users and other social strength measures of user experience of added-value for the retailers. Fig. 6 shows the social media insightsdashboardfor the jewelry e-commerce website.

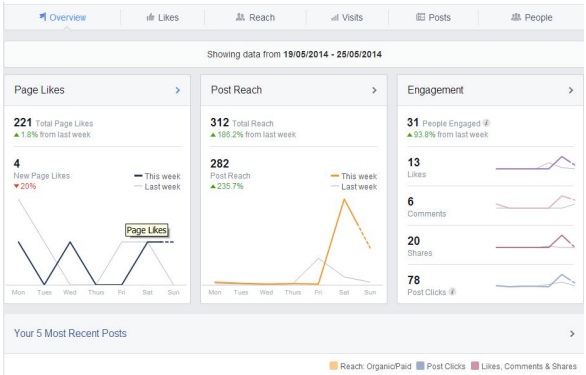

Fig. 6. Social media insights dashboard for an e-commerce store

Several reporting features of BI can be utilised by the recommender system of an e-commerce store to continuously monitor and evaluate the performance of the website and their business key performance indicators (KPI).Such metrics and visibility about the performance of the store serve as change-enablers that help businesses to dynamically react to the changing customer needs from time to time.

CONCLUSIONS AND FUTURE WORK

A significant amount of research has exploredthe five types of recommender techniques (collaborative, demographic, content, utility and knowledge based) and various hybrids. Particularly lacking in literature is the use of Business Intelligence for better decision making by the user as well as businesses, which has been recently in limelight with technology advancement in BigData. In this paper, we proposed a framework for Business Intelligent Recommender System, which can make use of OLAP reporting tools with Big Data to monitor business performance. The motivation of such a system would be to intelligently use huge data on the web for providing a more trusted and context-aware set of recommendations to the users coming from dynamically changing social and demographic circumstances.We have discussed the components of the proposed recommender system and its applicationto a B2C e-commerce website as an example. The effectiveness of the framework would be studied by applying it to many real-world businesses with different performance metrics as a future work.

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