International Journal of Engineering Research & Management Technology ISSN: 2348-4039
January-2017 Volume 4, Issue-1
Email: editor@ijermt.org www.ijermt.org

A HYBRID APPROACH FOR RECOMMENDER SYSTEMS WITH BIG DATA

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ABSTRACT: Recommender systems are one of the most common and easily understandable applications of big data. The most known application is likely Amazon, Snapdeal and Flipcart's recommendation engine, which gives to clients a customized i.e. personalized webpage from its database when they visit Amazon.com, Snapdeal.com and Flipcart.com respectively.
However, e-commerce business organizations are by all account not the only ones that utilize recommendation engines to influence clients to purchase extra items. Recommender frameworks can be utilized as a part of different businesses and in addition have distinctive application, from recommending music and occasions to items and dating profiles
Let's have a look what recommender systems are and how can you apply them in your organisation.
KEYWORDS: Big data, user, hybrid recommendation, collaborative.

SCIENCE BEHIND RECOMMENDATION

The major ways most of recommendation engines work based on the following methodologies:

(A). Content-based filtering method: Content-based filtering methods are based on a description of the item and a profile of the user's preference [1]. These algorithms try to recommend items that are similar to those that a user liked in the past (or is examining in the present). In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended [2, 3]. This approach either rely on the properties of the items that each user likes, discovering what else the user may like as shown in the below fig.1.

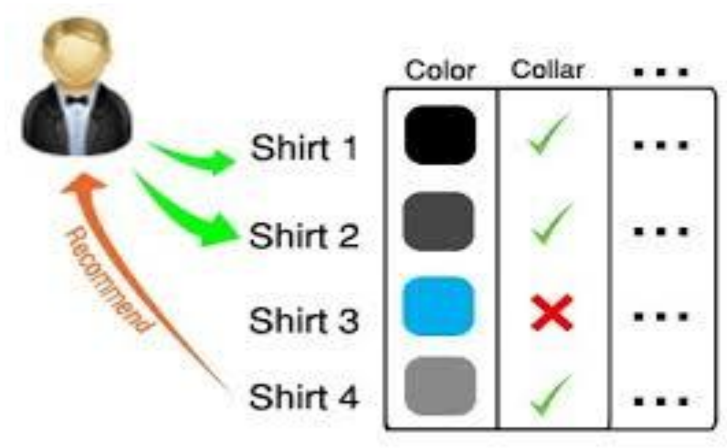

Fig. 1: Content-based Filtering

The fig. 1 shows that there are four shirts with different features (like colour, collar, ...). Here the user liked to the Shirt 1 and Shirt 2 (Both Shirt 1 and Shirt 2 have collar features). As per Figure 1, Shirt 4 has also the Collar feature, So, the content based approach recommend the Shirt 4 to the user which is similar to the Shirt 1 and Shirt 2(as all three shirts-1,2 and 4 have the collar feature)

(B). Collaborative filtering method: This method try to predict the utility of items based on the items previously liked or rated by other similar users. The utility of u(c,i) of item i for user c is estimated based on the utilities u(c,i) assigned to item i by those users cj ∈ C Who are "similar" to user c.[5,6]

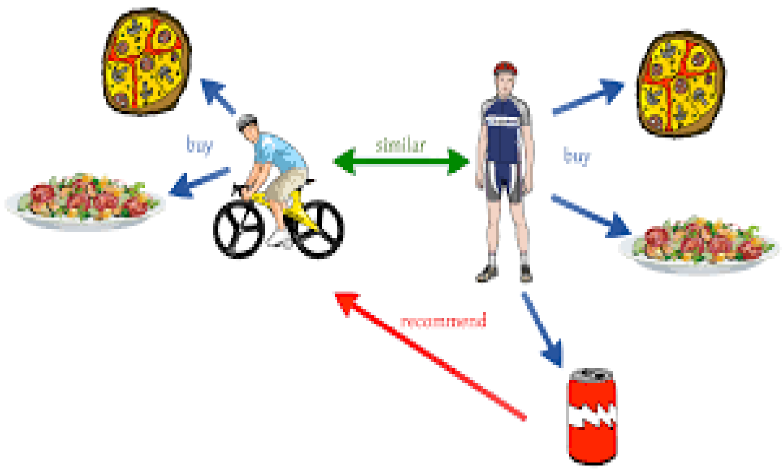

Fig. 2: Collaborative filtering

Fig. 2 shows that there are two persons both liked the similar items (like pizza and namkeen dish). Here the 2nd person (who is in stand-up form) also liked the Cold drink. So, collaborative filtering methods recommend the cold drink to the other user (who is on bicycle)

(C). Hybrid recommender Method: This approach combining collaborative and content-based filtering to build a more prosperous recommendation as shown in the below **fig. 3**

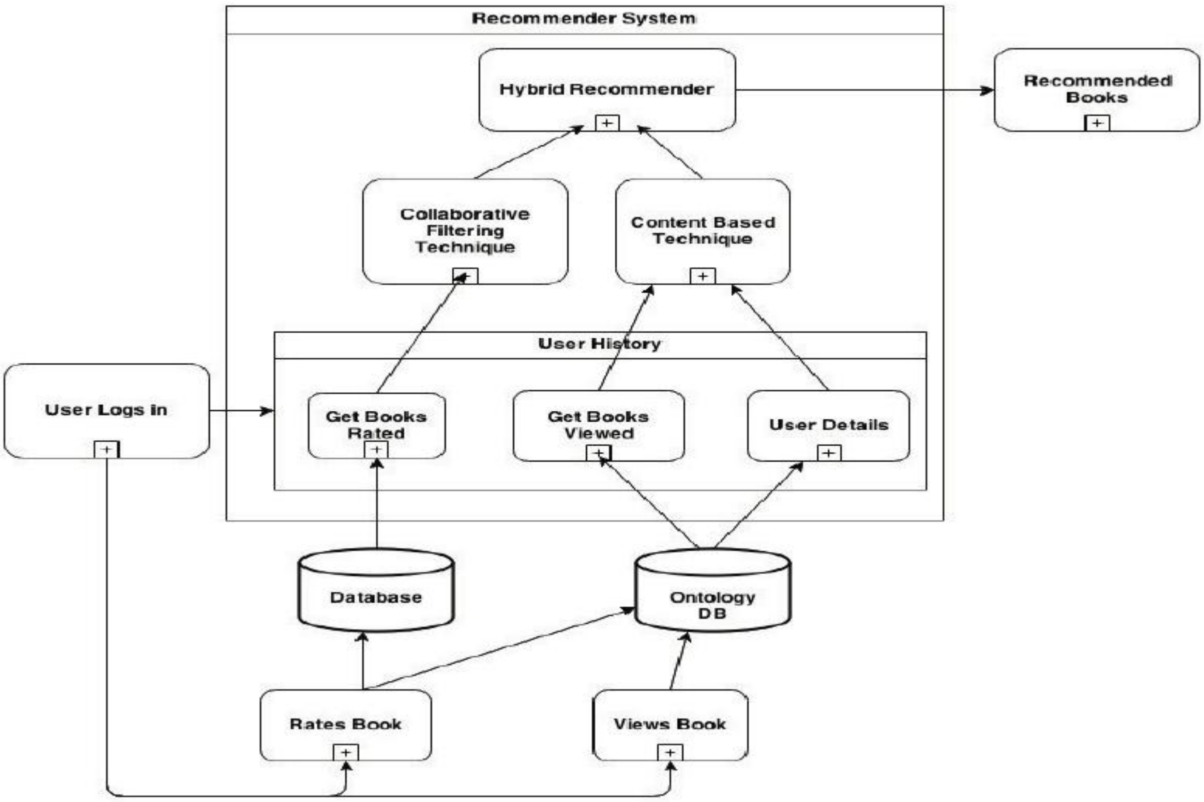

Fig. 3: Hybrid recommender Approach

Fig. 3 shows that recommendation makes by comparing the reading and searching habits of similar users (i.e., collaborative filtering) as well as by offering books that share characteristics with books that a user has rated highly (content-based filtering).

Types of data used by recommendation engines:

(1) User behaviour information:

- ***log on-site activity:*** In this activity user directly search, click on links/ pages and view the item(s) which gives to clients a customized i.e. personalized webpage when they visit Amazon.com, Snapdeal.com and Flipcard.com respectively[8].
- ***off- site activities*:** This activity refers to tracking clicks in emails, in mobile applications and in their push notifications [11].

(2) Specific thing points of interest: The following are the things in which a user has interest such as:

- category
- description
- price
- rating
- etc.

(3) Logical information

- current area/ location
- device used
- referral URL.

All the three information sources are similarly important for a predictable operation of all above three sorts of approaches [14,15]. Keeping in mind the end goal to get full photo of your client you ought to know about not just what he or she is survey on your site and your competitors' one, additionally how regularly, from which area and on which gadgets [17]. Having this data conveys you more like 36% expansion in deals, which Amazon experienced firsthand after recommendation engines were actualized or implemented on their site [20]

WHY INCORPORATE RECOMMENDER SYSTEMS

A recommendation engine is a feature that filters items by predicting how a user might rate them. Recommender systems have proved themselves efficient in the following areas[22]:

- It solves the problem of connecting your existing users with the right items in your massive inventory
- increase the number of items sold;
- sell more diverse items based on recommendation.
- increase the user satisfaction by providing more relevant choices.
- better understand what the user wants.

CASES OF RECOMMENDATION ENGINES SET TO WORK

(1). Customized item suggestions/recommendations: Such engines help to comprehend the inclinations and intent of every visitor and demonstrate the most pertinent suggestion type and items continuously. Suggestions enhance as the engine adapts more about every visitor [23].

(2). Website personalization: Recommendation System permits to Increase deals i.e. sales and conversions by segmenting and focusing on visitors with continuous customized messages and offers.

(3). Real-time notifications: Such engines help brands build trust with their customers and create a sense of presence and urgency while showing real-time notifications of shoppers' activities on the website[24].

Customized unwaveringness projects/programs and offers

Number of studies demonstrates that users or visitors are more keen on customized i.e. personalized offers than cookie-cutter solutions, which is particularly valid for dependability or loyalty programs [25]. Such engines can tweak proposals in light of continuous connections with every client or user. Information examination calculations are centered on various item classes with various buy conduct and the joining of relevant data, which enhances recommendation i.e. proposal quality.

Recommendation engines are at the upfront of prescient promoting. The key point is that they can be used in practically every industry to upgrade and enhance client experience.

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