



e-ISSN: 2319-8753 | p-ISSN: 2320-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Issue 4, April 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.512



9940 572 462



6381 907 438



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A Comprehensive Study on Book Recommender Engine

Reeba M Khan

Student, Post Graduate Department of Information Technology, S.S. and L.S. Patkar College of Arts and Science and V.P. Varde College of Commerce and Economics, (Affiliated to University of Mumbai), Mumbai, India

ABSTRACT: We live in a time of technological advances, the age where data has become fuel. However, looking at the excessive amount of data availability whether, in terms of structured or unstructured data, there has been an overburden made on selection and accessibility of desirable data. It has been a regular practice of information retrieval systems to tackle issues like prioritization and personalization. This has led to an urge for heightened demand for recommender systems. Recommendations have a much significant influence in our lives whether it be for any smallest thing that we purchase or even as huge as a venture that we might do. Suppose if we want to search for something, a sensible primary step is to ask Wikipedia, and that is what a ton of people would agree to. Recommender systems are systems that help users quickly show what they are looking for and assist them in finding new or comparatively similar items that they may like. Now, the primary reason why many individuals consider recommender systems are reliant on either “money” and/or “curiosity” and/or “need to examine similar interests”. A well-built recommender system can aid in a brilliant user experience, which is the reason they are profoundly significant in current society. Given the plethora of choices of books to look over, readers are regularly confused and hesitant on what book they should read next and this ends up being a standard incident for the person who is continually in search of reading the books. The following research paper focuses on providing a complete overview of book recommender engine starting from datasets available up-to the evaluation metrics that must be used.

KEYWORDS: books, recommender system, recommender engine, recommendation, user, content-based recommender, collaborative filtering, hybrid, filtering, similarity.

I. INTRODUCTION

Recommender systems are information filtering systems that manage the issue of data over-burden by sifting the significant data out of a large amount of information according to users' preferences. Such frameworks can foresee whether a specific user would prefer an item or not depending on the users' profile. A recommendation service is a computer-implemented service that simply recommends items from a database of items. The basic idea of recommender systems is to utilize various sources of data to infer customer interests where the entity to which the recommendation is provided is referred to as user, and the product being recommended is referred to like an item and hence recommendation analysis is often based on the previous interaction between users and items, because past interests and proclivities are often good indicators of future choices [1]. To state more precisely, a recommendation system is an intelligent computer-based technique that predicts based on users' adoption and helps to pick up items from a vast pool of data.

It is observed that recommender systems are quite frequently implemented using search engines indexing non-traditional data. They are beneficial to both service providers and the users as they reduce the selection time in any environment and also reduce the cost of transactions and time invested in finding items. These systems have also been proved to improve the decision-making process as well as the quality [2]. The fundamental principle of recommendations is that critical dependencies exist between the user and item-centric activity. They can also be learned in a data-driven manner from the rating matrix and the resulting model is then used to make predictions [1]. It is a fact that recommender systems are beneficial to both service providers and users [2]. Not just limited to that, but these engines or systems allow its users to move beyond the catalog searches and explore through a broader horizon.

II. RECOMMENDER ENGINE MODELS

Before deciding to work with any recommender engine it is important to choose the right recommendation model to increase the efficiency, accuracy and interactivensess of the engine.

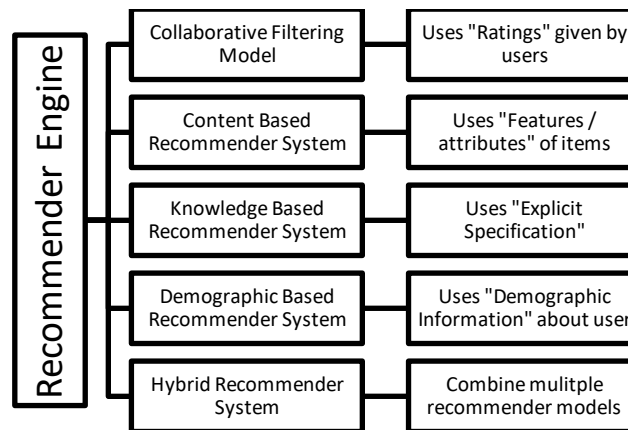


Fig. 1. Types of recommendation engine models

A. Collaborative Filtering Recommender System

Collaborative filtering models use the power of the ratings provided by multiple users on each book to make recommendations by designing the underlying rating matrices [1]. It is a domain-independent prediction technique for content that cannot easily and adequately be described by metadata and thus recommendations given are more generally either prediction or recommendation [2]. The quality of recommendation given by such a filtering method is directly proportional to the size of the rating dataset as therefore it suffers from a cold start as with fewer ratings it gets difficult to categorize items [4]. It generally performs filtering by calculating the similarity score between users and then based on the similarity score predicts the ratings and finds the most similar book [5]. To compute the similarity between users in collaborative recommender systems, a variety of approaches can be used and they are Pearson co-relation co-efficient, Spearman co-relation, Cosine similarity, Jaccard coefficient, and many more [8]. The effectiveness of collaborative filtering technique suffers from problems like data sparsity, cold-start and scalability [6]. The most widely used algorithms for collaborative filtering recommender system are as follows:

- Nearest Neighbor - kNN
- Matrix Factorization - Singular Value Decomposition (SVD) or SVD++ given as: $X = U S V^T$

B. Content-Based Recommender System

In content-based recommendation methods, the utility of an item for any user is estimated based on the utilities assigned by the user to items that are similar to the item [9]. These are based on a single user's interactions, preferences and generally require that the item include some form of content that is amenable to feature extraction algorithms. The descriptive attributes of items called "content" are eventually combined with ratings and buying behavior of users, and finally, this "user-specific" model is used to predict whether the corresponding individual will like an item for which her rating or buying behavior is unknown [1]. With this approach, the more information user will provide to the system model, the more accurate will it be. The only drawback here is the need to have an in-depth knowledge and description features of items in the profile. CBF suffers from problems like limited content analysis, overspecialization, and new users [11]. This is based on reclamation, analysis, and filtering information [12]. Content-based recommenders use various types of algorithms to model relationship and makes recommendation by learning the underlying model with either statistical or machine learning techniques. Those models are as follows:

- Vector space model - Term Frequency – Inverse Document Frequency (TF-IDF)
TF – IDF = TF * IDF

Where,

$$TF(t, d) = \frac{f_{t,d}}{\sum_{t \in d} f_{t,d}} \quad IDF(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

- Decision Trees

- Probabilistic model - Naïve Bayes

$$P(X|Y) = \frac{P(Y|X) P(X)}{P(Y)}$$

- Artificial Neural Networks [2]

C. Knowledge-Based Recommender System

This type of recommender system makes use of the knowledge about users and products for generating a recommendation, focusing on the user's interest in any particular set of products and checking whether the recommended product meets user requirements or not [12]. The core basis of these systems is explicit knowledge about item assortment, user preferences, and the criteria they use for making any further recommendation. These recommender systems are particularly useful in the context of items that are not purchased very often i.e. for items whose sufficient ratings may not be available for the recommendation process [1]. It acts in such a way that it prompts the user to give a continuous set of guidelines on what exactly the results should look like. It is considered that such systems are based on the concept of "Tell me what fits my needs" i.e. system gets the user requirements, matches it with its knowledge base about that particular domain, and recommends items that are most appropriate for the user [14].

D. Demographic Based Recommender System

Demographic-based recommender systems are justified on the principle that individuals with certain common personal attributes like age, country, etc. will also have some common preferences [8]. It is believed that demographic filtering or demographic recommender systems are an extension of traditional collaborative filtering techniques as they use similarity-based on users' profile and demographic segment [9]. An early recommender system, referred to as Grundy, recommended books based on the library of manually assembled stereotypes and since this system used characteristics of the user, it is observed to be belonging to demographic-based recommender systems [1]. For such a situation where demographic information is required, privacy could be a matter of concern. This type of recommender system can be often used as one of the methods to solve the problem of cold-start user and cold-start item [12].

E. Hybrid Recommender System

There exist various scenarios wherein more than one type of recommendation is either needed or is applicable as the system might have many components which need recommender engines and thus the only option that remains is to create a "hybrid". The basic idea behind the hybrid recommendation is that integrating different recommender system methods will improve and provide more enhanced recommendations than applying a single technique [7]. This technique is a result of the combination of recommender technique A and B, uses the benefits of both, and assures the removal of limitations of both the techniques to a large degree. Hybrid recommender systems are closely related to the field of ensemble analysis in which not only the power of multiple data sources is combined but they are also able to improve the effectiveness of a particular class of recommender systems [1]. These models usually based on bioinspired or probabilistic methods such as genetic algorithms, fuzzy genetic, neural networks, Bayesian networks, clustering, and latent features [8]. One of the biggest advantages of these systems is that they are capable of overcoming the grey sheep problem and sparsity problem [12]. Such systems can be augmented by knowledge-based techniques like case-based reasoning to improve the recommendation accuracy of traditional recommender systems [9]. Following are the most commonly used methods in building hybrid recommender systems: weighted, switching, feature combination, cascading, feature augmentation and meta level [2][6][7].

III. NEED OF BOOK RECOMMENDER SYSTEM

Books are believed to be man's dearest friend and in the period we live in today, which sees the nonstop turn of development and dynamicity, it has led to an expansion in the desire of enhancing knowledge through books not just academics as well as from general angle. Reading books is one of the most important aspects of life as it enhances physical as well as mental health, improves vocabulary, improves the brain's signaling process, builds up memory and knowledge. Also, many pieces of research indicate that reading promotes the human mind's growth. According to an investigation held in 2013, wherein the participants were requested to read the book for 9 days and their brain performance was estimated with the help of MRI scans, it was found that as participants read further, their brain signaling were getting influenced and the connectivity was found to have risen especially in the somatosensory cortex – a region of the brain that gets stimulated by sensations [20].

One key inspiration driving why we need a recommender system in present-day culture, is because individuals have an excessive amount of alternatives to pick and use from because of the commonness accessible on the web. There are more than sufficient books in a variety of forms, belonging to various domains, dialects, and categories like fiction,

non-fiction, life stories, comic, horror, mystery, action, science fiction, and so forth. As the availability of options increases, the more troublesome and tedious it becomes to choose one explicit book. Another motivation for focusing on recommender engines is that these are believed to be quite possibly the most important applications of machine learning and artificial intelligence. Book reading is a very optimistic hobby yet the response to this question “Which book next?” is a troublesome one to answer hence, in such cases usage recommender engine suits to be the best plan. Thus book recommender engine will enable in giving the best, precise and appropriate book dependent on users’ likeliness and holds the capability to dispose of off the confusion of choice.

IV. DATASETS EXPLORATION

For the book recommender system, various datasets are available publically which can be used for providing recommendations on the available data. These datasets play a very important role in the better functioning of any machine learning model. The more the data available, the more can be fed into the model and the better will be the performance and results. But many researchers are not aware of the availability of free datasets and application programming interfaces (API) available for book recommendation [3]. Following are some of the most commonly used datasets that easily available on the web for anyone to use.

A. Amazon US reviews dataset

The “amazon US reviews” also known as “Amazon customer reviews” dataset is a rich source of information that is publically available for the purpose of academic research. There are three different version of datasets available in this for books i.e. amazon_us_reviews/Books_v1_00, v1_01 and v1_02. The dataset consists of reviews of the books in the US marketplace. [22].

B. The bookshop dataset

“The Bookshop” dataset was created by Tableau Desktop 2020.2 to showcase the new data modelling capabilities for combining data. The version of the dataset is 2021.1. The dataset consists of 13 different tables within it with each table having its own attributes respectively. The tables are Book, Info, Edition, Publisher, Awards, Checkouts, Ratings, Series, Author, Sales Q1, Sales Q2, Sales Q3 and Sales Q4. The dataset consists of plenty of analytical scenarios and exploratory fields [23].

C. Goodreads dataset

The “Goodreads” dataset is a huge repository of books with information in terms of demographics, ratings counts, reviews and much more. It includes attributes such as bookID, title, authors, average_rating, isbn, isbn13, language_code, num_pages, ratings_count and text_reviews_count. The dataset can be extracted from the available goodreads API and can also be found on many platforms.

D. Project gutenburg dataset

“Project Gutenberg” is considered to the largest and the only one that has collections of over 30000 free electronic books in 50 different languages and rest 75000 ebooks in 100 languages are available. The dataset can accessed without any hassle. It is a clean and ready to use corpus that contains 3036 ebooks authored in English by 142 writers implying a very good set for making recommendations [3].

E. Book crossing dataset

“Book-Crossing” dataset was mined by Cai-Nicolas Ziegler and DBIS Freinburg. The dataset is freely available for the purpose of research. It contains around 278,858 anonymous users who provided in total 1,149,780 ratings including both explicit as well as implicit and around 271,379 books. It consists of three tables namely users, books and book-ratings each table having furthermore its attributes [25] [26].

F. Goodbooks 10k dataset

The “Goodbooks 10k” dataset consists of ten thousand books with over one million ratings which imply a deep repository for analysis and functioning of recommender system. The dataset comprises five tables such as books_tags, books, tags, tags and to_read. All these books have also been marked to read them by a specific user in the coming future [27].

V. SOURCES OF INFORMATION AND EVALUATION METRICS

For providing the recommendations for books, various sources of information are required on which the recommender model would be working. These sources of information are as follows:

- Book Ratings – Ratings are one of the most commonly used sources as they are given for each book by the users who must have read it earlier. The foundational collaborative filtering algorithm filtering tries to find similarities in users by correlating the ratings [21].

- Users preferences – Depending on what the user might like based on the history of users' access, the relevance of any item, or any statement made by the user on his/her preference. This source can sometimes create ambiguity if the information isn't stated well.
- Ranking – Ranking can be one of the very most important sources of information as it concentrates on an overall demographic status such as user profile, likes, dislikes, time spent by user, or any social network, etc.
- Keyword in books – There are certain keywords or specific stop words present in books that help to maintain a correlation for the recommendation. A social tagging system allows users to attach tags to the items that users share on a larger platform as they have the potential to improve web search [21].

Usage of evaluation metrics for any machine learning model is essential as they ensure the model's precision in terms of operation and yielding optimal solutions. Following are some of the evaluation metrics that can be used to evaluate the recommender system.

A. Coverage

Coverage refers to the percentage of items present in the training dataset that the recommender model is able to recommend to the testing dataset. It is the proportion of items that recommender system is able to recommend, sometimes also called as "catalog coverage" [21]. High coverage is important because it increases the number of recommendations a user can receive. [15]

B. Accuracy

Accuracy is one of the evaluation metrics used in case of evaluating classification-based machine learning models. This metric tells us how many times out of the total executions did our model got accurate and right predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where,

TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

C. Precision

It is a performance metric that measures the number of correctly classified instances by the model out of all instances that the model gave as result.

$$Precision = \frac{TP}{TP + FP}$$

D. Recall

Also called as "sensitivity", is the fraction of retrieved instances among all the relevant instances

$$Recall = \frac{TP}{TP + FN}$$

E. Fscore

It is a metric that describes the performance of a model and it is calculated as the harmonic mean of precision and recall.

$$F = 2 * \frac{Precision * Recall}{Precision + Recall}$$

F. Area Under the ROC Curve (AUC)

AUC is an evaluation metric for recommender systems that measures the ability of the classifier to differentiate between classes and calculates the area underneath ROC (Receiver Operating Curve). Higher AUC indicates higher model performance.

G. Mean squared error(MSE)

The mean squared error is a model evaluation metric often used to measure the mean between the squared difference of predicted values and actual values.

$$MSE = \frac{\sum_{i=1}^n (S_i - O_i)^2}{n}$$

Where,

O_i = Observation and S_i = predicted values

H. Root mean squared error (RMSE)

The root mean squared error is a standard used to measure the error of the model in predicting quantitative data. It is a good measure of accuracy, but only to compare prediction errors of different models for a particular variable.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2}$$

I. Mean absolute error (MAE)

The mean absolute error in the recommender model evaluation is a metric used to find the mean difference between the true value provided by the user and the predicted value given by the recommender system for any instance.

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n}$$

Where,

x = true value, y = predicted value, n = Total number of data points

J. Novelty

Novelty can be defined as the difference between present and past experience i.e. the relevance of recommendations. This is metric that is used to evaluate the recommender systems performance when considering the drift in users' preferences over time. [21]

VI. RELATED WORK

The most notable studies are focused on books, music, television and e-commerce [10]. Many types of research on book recommendations have been done with a motive to always develop the best model in terms of accuracy, performance as well as recommendation. Manisha Chandak, Sheetal Girase, and Debajyoti Mukhopadhyay proposed a hybrid technique for better optimization of the book recommender system. Their model was a combination of collaborative and content-based filtering. In addition to that demographic features of users were used to generate similarity among users [4]. Adli Ihsan Hariadi and Dade Nurjanah proposed a hybrid attribute and personality-based recommender system for books wherein they applied hybrid attribute method MSV-MSL to perform recommendation along with which they also used personality factor for measuring similarity between users [5]. A web application named "Pickbooks" was presented by I. Petrovic, P. Perkovic, and I. Stajduhar, which helps the user to discover books as well as connect to his/her friends. One of the most interesting characteristic here was that the recommendations are mood-centric and the database was community-driven [11]. Praveen Mathew, Bincy Kuriakose, and Vinayak Hegde proposed a book recommendation system that was based on content-based filtering, collaborative filtering, and association rule mining to generate recommendations. They implemented this model in a web-based application for effective performance [16]. In the work presented by Shahab Saquib Sohail, Jamshed Siddiqui, and Rashid Ali, they focused on delivering book recommendations based on opinion mining i.e. FOMA which could recommend books to university students relating to their syllabi by extracting opinions from reviews and then calculating the opinion score [19]. In the implementation of MapReduce based recommendation system done by Joon-Min Gil, JongBum Lim, and Dong-Mahn Seo, they used keywords of the books that were very frequently accessed which represented features of big data and those keywords were mapped used along with MapReduce programming model on the Hadoop platform. This made much easier for users to rent book based on similarity [28]. BReK12 is a book recommender design presented by Maria Soledad Pera and Yiu-Kai Ng. BReK12 selects candidate books, assigns them a ranking score which is calculated as an aggregation strategy on content and readership similarity for books [29]. Commenders – book recommendation for online book communities was proposed by HyeaKyeong Kim, Hee Young Oh, JaChulGu, and Jae Kyeong Kim. They used collaborative filtering along with utilizing keywords of each item. The model first tries to extract information by finding neighbors and then generated a list of books by using CF. Furthermore, keyword matching is performed to discard irrelevant books [30].

VII. CONCLUSION

This paper has tried to provide a complete study on recommender engines or recommender systems specifically for the book as the number of readers and availability of books are increasing at a greater pace. Every type of recommender system has its advantages and disadvantages, it depends upon various factors like data, algorithmic model, etc. As hybrid recommender systems are produced by combining the traditional recommendation techniques i.e. collaborative filtering and content-based filtering in most of the cases, they can result in enhancing the quality of recommendation. The approach towards building the recommendation engines can improve the scalability and users' experience in searching through the catalog for any item. Hence, the upsurge in the adoption of artificial intelligence in the recommendation engine to offer personalized customer experience is expected to create lucrative possibilities for the various categories of recommender engines in the market.

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