International Journal of Research Studies in Science, Engineering and Technology
Volume 5, Issue 12, 2018, PP 64-71
ISSN 2349-476X
DOI: https://doi.org/10.22259/2349-476X.0512006

A Literature Survey on Recommender Systems

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ABSTRACT

This technical report examines the literature and explains the Recommender System ideas. A recommendation engine is a system that filters information to bring movies, music, books, news, photos, and web sites to the user. a set of tools to a user This data has been vetted to ensure that it is likely to pique the user's interest. This review is meant to be an important part of my overall project. Robert Gordon University, Aberdeen, conducts research at the IDEAS research facility. Please feel free to make suggestions, corrections, and contributions.

What is a Recommender System, and How Does it Work?

A recommender system is a system that filters information to provide products like movies, music, books, news, and photographs to the user.To a user, web pages are tools. A recommender system is a system that filters information and delivers it to a user in the form of movies, music, books, news, photos, web pages, and tools. This data has been vetted to ensure that it is likely to pique the user's interest. A recommender system's goal is frequently to "assist consumers in learning about new items and attractive ones among a plethora of options" [1] [2]. Information filtering systems, in general, strive to eliminate redundant or undesired data from a data set. They're aiming for delivering relevant information and decreasing information overload at the semantic level while enhancing the signal-to-noise ratio "It appears that the concept of'recommender system' changes depending on the context," according to Ujjin's [3] study of certain literature in 2001. Author. Some academics interchangeably use the terms "recommender system," "collaborative filtering," and "social filtering" [4] [5]. He "Others regard'recommender system' as a generic term," he says.

Methodology

Many different sorts of data can be gathered. "A simple taxonomy distinguishes content-based versus collaborative-filtering-based recommender [systems]" [1]:

The attributes are derived from the information item in a content-based method. Approach to collaborative filtering: the features are derived from the user's environment (social, user preferences, patterns, etc.) The cold-start problem is one of the major concerns with both systems. To gain access to the system, new users must first engage with it. The system becomes more efficient for their demands as their profile grows. [8] A hybrid method is frequently proposed, incorporating features from many sources. To avoid such constraints, collaborative and content-filtering methods are used.

A Content-based Strategy

The content-based method entails examining the content of the recommended items. Each user is given special attention. There is one. There is no presupposition of belonging to a group or a community [3]. The system operates mostly by analysing items and their proximity to other items. The user has chosen.

Information Filtering through Collaboration

[1] Collaborative filtering "looks like word-of-mouth recommendations." "Collaborative filtering" is "one of the most successful technologies for recommender systems," according to Herlocker et al. [7]. The origins of collaborative filtering systems can be traced back to older information filtering systems. Those systems were created with the goal of bringing only relevant information to the user based on their previous actions. constructing a user profile This system is based on the collection of taste data from a large number of people. Underneath it all is a sense of belonging. [3] It assumes that a set of users

will value products similarly and then attempts to "predict the unobserved preferences of an active user." Particular Benefits/Issues of the System Collaborative filtering with MovieLens [3] By asking questions, he creates a profile. the ability for users to rate movies Looks for things that are comparable. profilesHeuristic and stochastic models to boost your profile Collaboration is a common problem. filtering systems: an explanation recommendations.

Filtering that is Active (or Explicit Data Collection)

Because of its peer-to-peer matching strategy, active filtering is a way for collaborative filtering. Various peer profiles are linked to find others with similar interests. This strategy is founded on the idea that peers share information like ratings and compliments. a list of specific items It replicates friends promoting shops to one another in a natural way. This type of filtering is especially useful in. There are instances where people are unaware of the vast amount of information available to them. One of the primary benefits of active filtering is that the information rating is provided by a real person who has really seen the item interest. Another benefit of substantially social-oriented systems is that it allows willing people to be heard and contribute. Information that is really relevant .The biggest downside is that this approach necessitates user action, which makes the data more difficult to access. The biggest downside is that this approach necessitates user action, making data more expensive and infrequent to collect. Another disadvantage of requiring action is that the feedback offered may be skewed, for example, towards a bad or positive experience, depending on the intended customer. Another problem with those content filtering methods is the averaging effect that occurs. in some specific circumstances Over a large number of similar things, the system will be unable to distinguish between them. This As a result of the higher number of ratings, the most popular things are often recommended more frequently. The issue of the First-Rater occurs for new things that have never been rated before, and the Cold Start problem occurs for new users who have never had any preferences before.

Filtering that is passive (or implicit data collection The user collects information implicitly through passive filtering. Purchasing a thing is one example. repeatedly using, saving, printing, updating, and commenting on an item referring to a website or providing a link to one (in another context than only rating, for example social media) The number of times a particular item has been queried. To detect if the user is scanning, reading, or dealing with a document, time measurements are taken. The key benefit of passive filtering is that it increases the number of users that provide feedback. In reality, just a small percentage of the population of Users return to the system to rate items, but they must all login to access the item. During that time, they act in a certain way. Most likely, they will be able to share information on their area of interest.

Filtering based on items

Instead of users, items are rated and utilised as matching parameters in that filtering strategy. Users are presented with a list of items that have been grouped together. After then, users can compare and rate them. User choices are gathered voluntarily. These settings enable you to create groups. Users are categorised by their areas of interest. After that, the things are chosen based on the ratings of a comparable user.

Benefits and Drawbacks of Recommender Systems

Business Viability

On the Internet nowadays, there are a plethora of recommender systems to choose from. Many commercial websites create custom-made solutions. to assist their users in locating things and increasing sales MovieLens, LIBRA, and Dooyoo are three real-world systems that are frequently mentioned in the literature. Ujjin reviewed academic articles [3]. MacManus [9] analyses a couple others and adds Iskold's [10] [11] remark that there are "4 major methods for making recommendations:

- Personalized recommendations — make suggestions based on a person's previous actions.
- Recommendations based on the past behaviour of comparable users are known as social recommendations.
- Item recommendation - provide suggestions depending on the item.
- "A mix of the three ways mentioned above."

System	Features	ParticularAdvantages/Issues
MovieLens[3]	• Collaborative filtering • Builds a profile by asking the user to rate movies	• Common issue to collaborative filtering systems: explaining how recommendations are populated.
	• Searches for similar profiles • Stochastic and heuristicmodels to improve profile Matching.	• Herlocker et al. [12] introduces" explanation facilities for recommender systems in order to increase users' faithin the suggestions" [3]
LIBRA [3]	• Combines content-based approach and machine Learning • Uses Bayesian text-categorisation machine learning techniques to build models of user preferences relative to a specific item	• Explanations can easily be produced • Inappropriate to non-textual items (images, video, music clips)
Dooyoo[3]	• Gather qualitative opinions from users • Displays results in a similar way to search engines • Evaluates "usefulness" • Social approach: Creates groups of users with similar opinions.	• Easy to explain recommendations by using textual review • Not a fully automated system • Requires users to review and rate each individual item
Pandora [10] [9]	• Deep item analysis (Music Genome Project theory [13]) • User preference represented in term of a collection of item.	• Low cost of entry for the user (pick one artist or song, refine later). Music starts instantly.
Amazon [9] [10]	• Combined approach (personalised, social and item based) • Recommendation based on matching of: actual items, related items, items other user purchased, new release, related items to new release	• Pure commercial approach. Aims at making users add more items to their shopping cart. • Their algorithm apparently overcomes the new item problem. (Cold start) • Based on a decade of data and system improvement and refinements.
Google [9]	• Customise search results based on location and recent search activity ("when possible") • Customise results based on account history • Uses pages link structures (social recommendation) • Recommendation to closest match (Did you mean feature)	• Although their system is initially a search engine, some recommender systems features are integrated to improve the user experience and deliver "personalised recommendations". [9]
Del.icio.us [10]	• Tag based indexing (similar approach to Pandora's genes [10]) • Tries to match multiple tags • Heuristic based	• Self-organising classification of items [10]

RECOMMENDER SYSTEM ISSUES

MacManus has published a series of pieces in an online publication devoted to social technologies. In one of them, he discusses the current state of the environment. [14] Recommender systems. The lack of data is the first concern MacManus brings up. Because recommender systems are based on previous behaviours, they require a large amount of data on both those behaviours and the goods being recommended. [14] The amount of user, user data, and item data available to the system is frequently linked to the quality of recommendations. This is related to the cold-starting issue [8]. This occurs when a new person or item is added to the system. To match other data and receive/be recommended, a profile must first be created. The needed amount of data includes not only the number of items and users, but also the number of variables extracted. [14] User profiles can have a lot of attributes, and a lot of them will have incomplete or sparse data. [12] This makes it tough to identify profiles that match. Using stochastic or heuristic approaches, this can sometimes be overcome. Another option is to utilise a user-evolved algorithm. [3] "Most existing systems employ typical closest neighbour algorithms that consider only'voting information' as a feature on which comparison between two profiles is made [4]," according to Ujjin. He suggests a hybrid system (content and collaboration) that takes into account several factors such as the The data in recommender systems is frequently updated on a regular basis. According to Edmunds [14], systems are "inclined towards the old and have trouble exhibiting new." Because there will be more data accessible on the old things, new items will simply be less suggested. Only preference values are used in pure collaborative filtering systems (ratings). The penetration of each item is then determined by the ratings of other users. This can result in an averaging effect. Overall, the most popular things will be recommended more frequently, boosting their visibility and, as a result, their consumption. This leads to more item ratings and a worsening of the averaging effect on recommendations. Another difficulty, which is tied to the preceding one, is users' shifting intentions. A user can be looking for one thing one day and something completely different the next, possibly for a buddy. [14] It's also tough to categorise or associate some unusual products. It's referred to as "Unpredictable Items" by MacManus. This has something to do with the fact that

Human tastes change throughout time and from one situation to the next. "Many researchers discover that their newest algorithms give a mean error of roughly 0.73/5 on movie rating datasets," according to Herlocker et al. [7]. They think that there is a "magic barrier" that prevents greater accuracy due to the natural unpredictability of consumer preferences. They quote Hill et al., who found that "when asked to review the same movie at different periods, users gave contradictory evaluations." According to Hill et al. [15], an algorithm cannot be more accurate than the natural variance in the user's evaluations.

The scalability issue is more relevant from an algorithmic standpoint. According to Soboroff [16], such concerns, as well as others, were initially detected about 1994. (sparse ratings, handling of implicit ratings, content-collaboration hybrid approach, and commercial viability). "Expectations were pretty low [...] 10,000 users and 100 predictions per second was a decent performance and 'better than random' was successful" [16] when the concept of Recommender Systems first arose in 1992. This problem is confirmed by Konstan and Riedl[17], who state that "conducting an experiment to test a hypothesis relating to recommender systems requires too much experimental set-up and too much lag time," indicating a lack of "technology, tools, testbeds, and data sets needed to efficiently conduct research." "Many collaborative filtering techniques have been created expressly for data sets where there are many more users than objects," Herlocker et al. write in [7]. Such algorithms could be useful.

PRINCIPLES OF OPERATION TRENDS

The main idea is to compare user profiles to known reference features in order to estimate how satisfied a user will be with a particular item recommended. Data collecting can be done in a variety of methods, both implicit and explicit (examples).

Explicit Implicit

Rate the items you've looked at.

Rank the length of time spent watching.

Choose between two options.

Purchased item

Choose from a list of options.

Items that were usedAnalyzing Social Networks.

The information gathered is compared to similar information gathered from other users. The user is then presented with a list of suggested things.In recent years, a variety of approaches of comparing closeness have emerged. The Nearest Neighbourhood technique [18] [19] is still one of the most prevalent ways in commercial systems.

A particular preference can be discovered using a Pearson Correlation on the user preference data of the top-N neighbours. Ujjin [3] has proposed an evolution-based adaption of this approach. This is a hybrid system (content and collaboration) that takes into account a variety of factors, like the user's age, gender, movie genre, and so on. The features that are significant for the comparison are then selected and weighted using evolutionary algorithms. It aids the system in producing customised solutions for each user by adjusting the weight of each parameter required for correlation. The dynamic combination of variables appears in a variety of ways.

Delgado "introduced a prediction method that integrates the correlation prediction with a weighted-majority voting mechanism," according to [16]. A similar technique might potentially be used to weight communities rather than users, according to the article. Claypool is said to have presented a method in [16] that uses a combination of content average and collaborative prediction weighted at the user level. Initially, content was reported to perform better, but as the system learned, collaboration became increasingly crucial. Among early systems, Oh [1] mentions the employment of neighborhood-based methods like the Pearson correlation coefficient as a common and conventional methodology.

Alternative methods have now been developed, such as Ansari et alBayesian .'s preference model approach [20]. The following advantages of this strategy may be seen: user heterogeneity, integration of expert and user information sources, explainability, and the use of a regression model [1]. (Markov chain Monte Carlo [20]). Condliff offered a "Bayesian model that incorporates material and collaborative information," according to [16]. For each user, the model employs a naive Bayesian classifier based on item attributes. After that, a regression model is used to integrate the classifiers in order to approach maximum covariance. Mooney is believed to have demonstrated a book recommender system employing "text categorization methods on the item information and reviews" and other techniques in [16]. This was a "bag of words" paradigm that was semi-structured. Breese et al. presented utilising information retrieval techniques an alternate weighting approach [1] in [4]. Demir et al. present a Multiobjective Evolutionary Algorithm for Web Searching in [21].

They use what they've learned about grouping with Evolutionary Algorithms [22]. "The clustering problem with automatic determination of the number of clusters is better tackled with several objectives," according to Demir et al. [21]. They want to improve this clustering algorithm's fit so that they may utilise it as an off-line modeller for their recommender system. The optimization of the computation required for recommender systems is another area of interest. According to Goldberg [16], he offered a "method to reduce the time required to compute predictions" by computing only the principal components of a ratings matrix off-line rather than a whole correlation matrix at the time of prediction. In [16], Herlocker is believed to have introduced a rating matrix application of clustering and partitioning algorithms with mixed results on prediction accuracy. The method could be "appropriate for parallelizing the problem without causing too much harm to [the] accuracy and coverage," according to the researchers. "All web recommendation systems are built of two components: an off-line component and an on-line component," according to Demir et al. [21]. They go on to say that usage patterns are derived off-line, and that the recommender system's performance is "dependent on how well the patterns are recovered from usage data" [21]. Recommender systems' scalability is also a hot topic. Herlocker et al. concluded in [23] that some "highly correlated users do not do well in forecasting the active user's preference ratings" [1]. Traditional recommender systems could be conceptually extended, according to Adomavicius et al. [24]. It might be conceivable, for example, to expand the typical memory-based collaborative-filtering strategy, which takes into account information such as time, location, and social interactions (for example, who is going to see the film to be recommended with the user). "Several business applications [...] are more complex than [the usual] movie recommender system, and recommendation systems would have to evaluate many more elements." [1].

ACCEPTANCE BY USERS

Oh [1] examines the literature on a user's acceptance of a recommendation. Felder and Hosanagar [25] assume that the chance of consumers adopting a recommendation is a stochastic process that is constant. "While this assumption of invariance simplifies the analytical and simulation models, in recurrent choices, decision makers adjust their trust toward the advisor based on the feedback of the quality of earlier guidance" [26], Oh [1] tampers this assertion. The lack of explicability is one of the most regularly cited issues in the research on recommender systems [1]. According to Herlocker et al. [12], most systems' black-box features preclude them from being used to higher-risk domains. A well-designed recommender system can be a strategic business benefit, and releasing the details behind the recommendations is frequently seen as a commercially sensitive activity. Users' likeness toward a recommender system is much higher for transparent suggestions than for non-transparent recommendations, according to Sinah and Swearingen [27]. According to Helocker et al. [7], incorporating explanation increases the acceptance of collaborative-filtering systems and expert systems in general. Wang and Benbasat [28], Buchana and Shortliffe [29], Ye and Johnson [30], and Yaniv [31] all agree. Consumers are more influenced by recommendations for experience items such as movies, music, and food, according to Senecal and Nantel [32], than for search products such as cameras, computers, and so on. They explain that experience items are more closely tied to taste and common qualities sought by similar customers, whereas goods recommendations are more closely related to facts. A'standard' product review will then be as useful as a suggestion for a good product. Recommender System Evaluation

"RECOMMENDER SYSTEMS HAVE BEEN EVALUATED IN DIFFERENT, OFTEN INCOMPARABLE METHODS,"

According to Herlocker et al. [7]. User feedback on the recommendation is one of the most common ways to evaluate a recommender system (rating). [3] This is, however, a costly process that cannot always be carried out because it requires the user to reconnect to the system for that specific purpose. Multi-fold testing on the supplied dataset can be used to replicate this. By their very nature, recommender systems can achieve a wide range of goals, including discovering good items, finding all good items, contextual annotations, sequence suggestion, browsing, assisting users, influencing users, and so on. This complicates the effort of comparing and evaluating different systems [7]. The majority of "conventional" evaluations will be ineffective for new systems. Herlocker et al. [7] specify the following domain features: User tasks are supported, and the content topic and context are supported. There is a demand for novelty as well as a demand for excellence. Granularity of actual user choice cost/benefit ratio of false/true positive negative.

THE FOLLOWING ARE SOME OF THE MOST COMMONLY UTILIZED MEASURES ACROSS TIME: [7]

Metrics of predictive accuracy: how closely the recommender system's anticipated ratings match the actual user ratings. The mean absolute error, for example, is the average absolute variation between a predicted rating and the true rating of the user. Metrics for Classification Accuracy: how often a recommender system makes the correct or erroneous conclusion. Precision and Recall, which are based on information retrieval techniques and measure the occurrence of relevant and non-relevant items, are two examples. [7] claims that recall is "nearly always impractical." Ranks Accuracy Metrics: a measure of a recommender system's ability to produce an item ordering that is similar to how the user would have arranged the identical items. The correlation between the variance of the system's result and the variance of what the user would have chosen is measured by the prediction-rating correlation. Distance-based Performance Normalized.

According to Herlocker et al. [7], "an growing knowledge that good recommendation alone does not provide users of recommender systems with an effective and gratifying experience" is emerging. They go on to say that the recommender system should deliver not only accuracy, but also utility. Coverage could be used to assess usefulness ("measure of the domain of items in the system over which the system can form predictions or make recommendations" [7]). Other measures [7] include learning rate (in the case of a learning algorithm-based system), novelty and serendipity (not recommending obvious items that all users would pick up anyhow), confidence (user confidence in the recommendation), and user evaluation (implicit or explicit).

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Citation: *Manchi Nandini et al, "A Literature Survey on Recommender Systems", International Journal of Research Studies in Science, Engineering and Technology. 2018; 5(12): 64-71. DOI: https://doi.org/10.22259/2349-476X.0512006*