The Trends in the Use of Recommender Systems

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Abstract

The aim of this study was to review the studies carried out on recommender systems. Various databases were searched for keywords “recommender systems”, “collaborative filtering”, and “content filtering”. These studies were shortlisted as per the year of publication. Studies talk about the use of internet and World Wide Web being the reason behind the use of recommender systems today. Due to the advent of plethora of e-commerce and leisure websites, social media and a variety of search engines being used around the globe by millions of users today, there is an overwhelming amount of information being generated every second. In order to save the users from this information overload, recommender systems use users’ choices and make recommendations to them. Many of the studies reviewed have discussed collaborative and content filtering in recommender systems. Studies have talked about concepts such as novelty, diversity, unexpectedness, memorization and generalization in connection with recommender systems. Some studies have also talked about the social media and recommender systems. Active learning is another concept covered by a few of the studies which have been reviewed in this paper.

Keywords: Recommender System, Review, Trends, RS

Introduction

Over the last decade, a wide variety of recommender systems (RSs) has been developed and used across several domains. According to Fernández-Tobías, Cantador, Kaminskas, & Ricci (2012), RSs are an active research field. RSs are being used successfully in numerous e-commerce and leisure websites such as Amazon, Netflix, YouTube, iTunes, and Lasf.fm. Most of these systems offer recommendations only for items from a single domain, e.g., Netflix suggests movies and TV series, and Last.fm makes personalized recommendations of music artists and compositions. In both cases the recommendations are computed using user feedback (ratings) about items in the target domain. In e-commerce sites like Amazon, nonetheless, it would be useful to exploit the user’s evaluations about diverse types of items in order to generate a more general model of the user preferences. In fact, there could be dependencies and correlations between preferences in different domains and instead of treating each type of items (e.g. electronics and music) independently, user knowledge acquired in one domain could be transferred and exploited in several other domains. Moreover, although it is not the main goal of cross-domain recommendation, a system could offer joint, personalized recommendations of items in multiple domains, e.g. suggesting not only a particular movie, but also music CDs, books or videogames somehow related with that movie (Fernández-Tobías, Cantador, Kaminskas, & Ricci, 2012).

There has been an overall acceptance of RSs in the social and business spheres. The recommendations made by the best of these RSs have also become significantly more accurate than they used to be previously (Adamopolous & Tuzhilin, 2015).

Despite this progress, the RSs have not yet met the consumer needs perfectly. According to the study by Adamopolous & Tuzhilin (2015), “there is still a long way to go in terms of satisfaction of the users' actual needs. This is due, primarily, to the fact that many existing RSs focus on providing more accurate rather than more novel, serendipitous, diverse and useful recommendations".

Methodology

In this paper, we will review some of the research studies which have been carried out on the subject of recommender systems. Towards this end, specific search terms were used in Google Scholar search engine, such as "recommender systems", "collaborative filtering", and "content filtering". The results of these searches were shortlisted as per the year of publication. For the purpose of this study, only studies published after 2000 were used, in order to review the studies on recommender systems.

Results and Discussion

According to Khusro, Ali, & Ullah (2016), the World Wide Web has brought about significant changes in the way people live today. This also affects the way people communicate. People use the Web as well as its technologies such as search engines to both search for and retrieve information. Due to this, the users who search for pertinent and credible information using the Web are burdened with information overload, which also adds up to cognitive overload. In order to overcome these challenges, a recommender system works as a helper in finding relevant and related items by making relevant suggestions to the users (Khusro, Ali, & Ullah, 2016).

Recommender systems help to overcome information overload by providing personalized suggestions from an excess of choices based on historical data. According to Fernández-Tobías, Cantador, Kaminskas, & Ricci (2012), for coping with information overload, recommender systems have been introduced to filter items – web pages, images, videos, audio – that are of low relevance or utility for the user, and which present only a small selection better suiting the user's tastes, interests, and priorities. Often these suggestions are presented while the user is browsing an information service, without the need for the user to make specific search queries, as is usually done in information retrieval systems (Fernández-Tobías, Cantador, Kaminskas, & Ricci, 2012).

The universal use of recommender systems in real world, such as eBay and Netflix, generates massive amounts of data at an extraordinary rate. The increasing popularity of real-world recommender systems produces data continuously, rapidly, and in large amounts. For example, more than 10 million transactions are made per day in eBay. Netflix gained more than three million subscribers from mid-March 2013 to April 2013 (Chang, Zhang, Tang et al., 2016).

Definition

A recommender system can be understood as a search ranking system, where the input query is a set of user and contextual information, and the output is a ranked list of items (Cheng, Koc, Harmsen et al., 2016). Given a query, the recommendation task is to find the relevant items in a database and then rank the items based on certain objectives, such as clicks or purchases.

According to Khusro, Ali & Ullah (2016), a recommender system is an "Information Retrieval technology that improves access and proactively recommends relevant items to users by considering the users' explicitly mentioned preferences and objective behaviors" (pg. 1179). Recommender systems are used in numerous domains including products, videos, images, articles, news and books.

According to the study by Christakopoulou, Radlinski, & Hofmann (2016), most academic work in the field of recommendation systems falls into two broad classes:

1) Collaborative Filtering: Collaborative Filtering begins with a set of user/item affinity scores. The basic assumption here is that two users who agree about one item are more likely to agree about another item (Christakopoulou, Radlinski, & Hofmann, 2016). According to the study by Elahi, Ricci, & Rubens (2016), in collaborative filtering recommender systems, user's preferences are expressed as ratings for items. Each additional rating encompasses the knowledge of the system and affects the system's recommendation accuracy. In general, the more ratings which are prompted from the users, the more effective the recommendations are (Elahi, Ricci, & Rubens, 2016). However, the usefulness of each rating may vary significantly as different ratings may bring a different amount and type of information about the user's tastes. Here, active learning strategies become useful as they can be used to choose items to be presented to the user for rating purposes. An active learning strategy identifies and adopts criteria for obtaining data that better reflects users' preferences and enables to generate better recommendations (Elahi, Ricci, & Rubens, 2016).

   According to Su & Khoshgoftaar (2009), Collaborative Filtering techniques use a database of preferences for items by users to predict additional topics or products a new user might like.
2) Content-Based Filtering: Content-based filtering models users by the characteristics of the items they like or dislike. Neither model represents how real people make recommendations, particularly in a cold-start setting where the person making a recommendation does not know a lot about the person asking for one (Christakopoulou, Radlinski, & Hofmann, 2016).

   According to de Gemmis, Lops, Musto, & Narducci (2015), content-based recommender systems (CBRSs) rely on item and user des criptions (content) to build item depictions and user profiles to recommend items similar to those a user has already liked in the past.

Streaming Data

In recommender systems, the data is temporally ordered, continuous, high-velocity and time varying, which determines the streaming nature of data (Chang, Zhang, Tang, et al., 2016).

Recommendation under streaming settings faces the following challenges simultaneously:

1) Real-time updating: One intrinsic characteristic of data streams is their high velocity. Hence, RSs requires instantaneous updates as well as response systems in place which would enable them to catch users' instant intention and demands.
2) Unknown size: New users as well as freshly posted items arrive continuously in data streams. For example, there were more than 21 million new products ordered on the main Amazon USA websites from December 2013 to August 2014. Hence the number of users and the size of recommendation lists are unknown in advance. Regardless of this, many existing algorithms assume the availability of such information.
3) Concept shift: Data stream evolution leads to concept shifts, e.g., a new product launch reduces the popularity of previous versions. Likewise, user preferences drift over time. The recommender system should have the ability to capture such signals and timely adapt its recommendations accordingly.

Unexpectedness

According to the study by Adamopolous & Tuzhilin (2015), one of the main areas of improvement in RSs which can "significantly contribute to the overall performance and usefulness of recommendations and that is still under-explored" is the concept of "unexpectedness". Usually, RSs recommend items which users are already familiar with; hence, these may be of no interest to them. For example, a shopping RS may recommend to customers products such as milk and bread. Although being an accurate recommendation in the sense that the customer will indeed buy these two products, this recommendation is of little interest to the shopper because it is an obvious one: the shopper will, most likely, buy these products even without this recommendation. "Therefore, motivated by the potential of higher user satisfaction, the difficulty of the problem and its implications, we try to resolve this problem of recommending items with which the users are already familiar, by recommending unexpected items of significant usefulness to them" (Adamopolous & Tuzhilin, 2015).

Novelty and Diversity

There is an increasing realization in the field of RSs that novelty and diversity are basic qualities which denote the effectiveness and added-value of recommendations (Castells, Vargas, & Wang, 2011). As per Vargas & Castells (2011), the RSs community has been paying increasing attention to novelty and diversity as key qualities beyond accuracy in real recommendation scenarios.

According to authors Castells, Vargas & Wang, extensive studies on measuring novelty and diversity are still rare in the field of RSs and the range of metrics described in relevant literature is considerably scant. In their study, Castells et al. say that novelty and diversity play a greater. A more central role in the recommendation context, "where the practical value and gain from recommendation are closely linked to the notion of discovery in most scenarios".

According to the study by Castells, Vargas, & Wang (2011), novelty and diversity are different but interrelated concepts. The novelty of any information can usually refer to how different it is from other pieces of information or with respect to what has been previously witness by either a specific user or by the community.

As per Castells, Vargas, & Wang (2011), diversity generally applies to a set of items, and is related to how different the items are with respect to each other. This is related to novelty in that when a set is diverse, each item is "novel" with respect to the rest of the set. Moreover, a system that promotes novel results tends to generate global diversity over time in the user experience; and also enhances the global "diversity of sales" from the system perspective (Castells, Vargas, & Wang, 2011). According to Vargas & Castells (2011), a common specific definition of diversity in the literature is the average pairwise dissimilarity between recommended items.

Memorization and Generalization

One challenge in RSs, similar to the general search ranking problem, is to achieve both memorization and generalization. According to Cheng, Koc, Harmsen et al. (2016), memorization can be defined as learning the frequent co-occurrence of items or features and exploiting the correlation available in the historical data. According to Cheng, Koc, Harmsen et al. (2016), generalization is based on transitivity of correlation and explores new feature combinations that have never or rarely occurred in the past. Recommendations based on memorization are usually more topical and directly relevant to the items on which users have already performed actions. Compared with memorization, generalization tends to improve the diversity of the recommended items. In this paper, we focus on the apps recommendation problem for the Google Play store, but the approach should apply to generic recommender systems (Cheng, Koc, Harmsen et al., 2016).

Interactivity

A lot of work has been done in the field of RSs which focuses on critique-based, constraint-based, dialog, utility-based recommenders. This emphasizes the importance of the property of interactivity in recommenders where the user has a more active role to play in relation to the recommendations (Christakopoulou, Radlinski, & Hofmann, 2016).

Social Media and Social Recommender Systems (SRSs)

According to Guy & Carmel (2011), in recent years, social media sites have become enormously popular. For example, photo and video sharing sites such as Flickr and YouTube, blog and wiki systems such as Blogger and Wikipedia, social tagging sites such as Delicious, social network sites such as MySpace and Facebook, and micro-blogging sites such as Twitter. Millions of users are on these websites every day, creating new and unique information every second. As a result of popularity of these websites as well as the variety and number of these sites, there are huge volumes of information which are created. This is huge challenge when it comes to the information overload which is being created (Guy & Carmel, 2011).

According to Guy & Carmel (2011), Social Recommender Systems (SRSs) have the objective of alleviating information overload which plagues social media users. These SRSs help users by putting together and presenting the most pertinent content which is attractive to the users. SRSs also aim at increasing adoption, engagement, and participation of new as well as existing users of social media sites. Recommendations of content (blogs, wikis, etc.) tags, people, and communities often use personalization techniques adapted to the needs and interests of the individual user, or a set of users (Guy & Carmel, 2011).

In their study, Guy & Carmel (2011) state that due to the benefits they offer, social media and personalized recommender systems can mutually benefit from one another. Social media introduces new types of public data and metadata, such as tags, ratings, comments, and explicit people relationships, which can be used to improve recommendations. Recommender technologies can play an important role in the success of social media applications and the social web as a whole. This can make sure that every social media user is presented with most pertinent content, which is attractive to the user on a personal basis (Guy & Carmel, 2011). Machine learning use is fairly common in social media (Rabbi, 2018). Recommender system utilise machine learning techniques.

Active Learning

If recommender systems are augmented with Active Learning (AL), it helps in the user becoming more self-aware of their likes and dislikes. Simultaneously, new information is also being provided to the system which could be analyzed for future recommendations (Rubens, Kaplan & Sugiyama, 2011). According to the study by Rubens et al. (2011), applying AL to recommender systems "allows for personalization of the recommending process, a concept that makes sense as recommending is inherently geared towards personalization. This is accomplished by letting the system actively influence which items the user is exposed to (e.g. the items displayed to the user during sign-up or during regular use), and letting the user explore his/her interests free" (p. 735). Various recommender systems have different objectives. Hence, there is need for their AL components to have different objectives as well. So, one AL method may be better for a particular task as compared to another. Usually, "AL does not consider the trade-off of exploration (learning user's preferences) and exploitation (utilizing user's preferences), that is, it does not dynamically assign weights to exploitation/exploration depending on system objectives. This trade-off is important because for a new user about which nothing or little is known, it may be beneficial to validate the worth of the system by providing predictions the user is likely to be interested in (exploitation), while long-term users may wish to expand their interests through exploration" (Rubens, Kaplan, & Sugiyama, 2011).

Though an objective of the recommender system is usually to provide accurate predictions to the user, "the system may also need to recommend items of high novelty/ serendipity, improve coverage, maximize profitability, or determine if the user is even able to evaluate a given item, to name a few" (Rubens, Kaplan & Sugiyama, 2011).

Conversation based AL: Generally, recommender systems have an open-ended objective - to predict items a user would be interested in, conversation-based AL converses with the user as a goal-oriented approach. Using the iterating of questioning, conversation-based AL tries to get a response from the user to best reduce the search space for quickly finding what it is the user seeks (Rubens, Kaplan & Sugiyama, 2011).

Conclusion

For the past decade and a half, due to the ubiquitous nature of the internet and the World Wide Web, there are millions of people who use leisure and e-commerce websites, social media platforms and search engines on a daily basis. This generates huge amounts of data and information per minute which, if not handled, would lead to information and cognitive overload in users. Recommender systems overcome this challenge. In this paper, we have reviewed studies which have explored recommender systems and their various aspects, related concepts, and definition, in order to gain a good understanding of how recommender systems function.

References

Adamopolous, P., & Tuzhilin, A. (2015). On Unexpectedness in Recommender Systems: Or How to Expect the Unexpected. *ACM Transactions on Intelligent Systems and Technology (TIST) - Special Sections on Diversity and Discovery in Recommender Systems, 5*(4), 11-18.

Castells, P., Vargas, S., & Wang, J. (2011). Novelty and Diversity Metrics for Recommender Systems: Choice, Discovery and Relevance. In *Proceedings of International Workshop on Diversity in Document Retrieval (DDR)*. Retrieved from http://ir.ii.uam.es/rim3/publications/ddr11.pdf

Chang, S., Zhang, Y., Tang, J., Yin, D., Chang, Y., Hasegawa-Johnson, M.A., & Huang, T.S. (2016). Streaming Recommender Systems. Retrieved from http://www.yichang-cs.com/yahoo/WWW17_StreamingRec.pdf

Cheng, H., Koc, L., Harmsen, J. et al. (2016). Wide & Deep Learning for Recommender Systems. Retrieved from https://arxiv.org/pdf/1606.07792.pdf

Christakopoulou, K., Radlinski, F., & Hofmann, K. (2016). Towards Conversational Recommender Systems. In *22nd ACM SIGKDD Conference on Knowledge, Discovery and Data Mining*. San Francisco, CA. Retrieved from https://www.kdd.org/kdd2016/papers/files/rfp0063-christakopoulouA.pdf

de Gemmis, M., Lops, P., Musto, C., & Narducci, F. (2015). Semantics-Aware Content-Based Recommender Systems. In F. Ricci, B. Shapira, & L. Rokach (Eds.), *Recommender systems handbook,* (pp. 119-159).

Elahi, M., Ricci, F., & Rubens, N. (2016). A survey of active learning in collaborative filtering recommender systems. *Computer Science Review, 20*, 29-50.

Fernández-Tobías, I., Cantador, I., Kaminskas, M. & Ricci, F. (2012). Cross-domain recommender systems: A survey of the State of the Art. In *Proceedings of the 2nd Spanish Conference on Information Retrieval*.

Guy, I., & Carmel, D. (2011). Social Recommender Systems. In *WWW '11 Proceedings of the 20th international conference companion on World wide web* (pp. 283-284). New York, NY, USA. Retrieved from http://ra.ethz.ch/CDstore/www2011/companion/p283.pdf

Khusro, S., Ali, Z., & Ullah, Irfan. (2016). Recommender Systems: Issues, Challenges, and Research Opportunities. In K.J. Kim and N. Joukov (Eds.), *Information Science and Applications (ICISA) 2016, Lecture Notes in Electrical Engineering 376* (pp.1179-1189).

Rabbi, F. A review of the use of machine learning techniques by social media enterprises. *Journal of Contemporary Scientific Research* (ISSN (Online) 2209-0142), 2(4).

Rubens, N., Kaplan, D., & Sugiyama. M. (2011). Active Learning in Recommender Systems. In P.B. Kantor, F. Ricci, L. Rokach & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 735-767). Springer.

Su, X., & Khoshgoftaar, T.M. (2009). A Survey of Collaborative Filtering Techniques. *Advances in Artificial Intelligence*, 1-19,

Vargas, S., & Castells, P. (2011). Rank and relevance in novelty and diversity metrics for recommender systems. In *Proceeding RecSys '11 Proceedings of the fifth ACM conference on Recommender systems*, (pp, 109-116). Chicago, Illinois, USA.