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Short Review Paper

Future of next generation recommender systems

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Abstract

With so many overwhelming information filtering-cum-accessing options from the Web, there is a need to sort, prioritize and offer relevant information efficiently in order to alleviate the problem of information overload. Till date, the exhaustive survey on recommender systems have unfolded their various contextual components like design types, filtering approaches, recommendation criteria, evaluation metrics, performance metrics and deployed application domains. Recommender systems have been reported to apply machine learning algorithms in evolutionary ladder on information, products and services of users' interest among the tremendous amount of available items. In this paper, we discuss various approaches used to build recommender systems, recommender system classification hierarchies as well as comparative interpretation among them.

Keywords: Recommender system model, Content-based, Collaborative, Hybrid, Classification hierarchy, Comparative studies.

Introduction

Recommender system can be perceived as a sub-realm of research in intelligent information filtering systems. While the existing surveys illustrate much on recommendation system models and ranking methodologies, our survey attempts to capture insights from newer recommendation system platforms that suffice challenging and exceptional application domains with acceptable performance metrics.

The criteria "personalization", "interestingness" and "usefulness" have helped researchers to better evolve the field of recommender system from information retrieval systems[1].

Traditional recommender systems are tuned to predict the interest of users based on the users' profile or browsing behaviours and user preferences. Going to the fact that recommender systems have been developed for wide-spectrum of application domains, intended to resolve multitude of Machine Learning tasks like group user recommendations, recommendation in social web, integration of FAQs and active sequences to recommended list of items as well as implementing security issues to develop PPRS, these generic algorithms can't be developed without borrowing concept & principles from multidisciplinary realms.

Hence implementation of any methodology and any participating domain of interest need to be evaluated. There are wide variety and multiple evaluation metrics available. Non-uniformity in the evaluation matrix made it necessary to build a uniform benchmarking of evaluation metrics. It has been anticipated that future generation recommender systems shall stress on answering to temporal aspects and action modes of implementing recommendation to the users.

Recommendation systems: case study

Many approaches have been applied to the recommender system to achieve peak performance but they all have strengths and weaknesses. Many times they are combined in different ways for the same. There are mainly three recommender approaches depending on the information used to drive it, Content-based, Collaborative and Hybrid. We give overview of the different types of RSs, a taxonomy provided by Isinkaye, 2015 that has become a classical way of distinguishing between recommender systems and referring to them[2]. Differentiate between six different classes of recommendation types. Some new recommendation systems types have been discussed.

Recommendation models: state-of-the-art: The Content based models build the personalized profile of the user based on the features of the items that are rated by the user, description of item and the user feedback as well to recommend similar items to the user interest or those items that has been liked by the user in the past[3]. Recommendation of items can only be done by matching up the features of the items against the set of properties of a content item[4]. Such systems are majorly used in recommendation of web pages, TV programs and news articles etc.

Collaborative Filtering Models utilizes the explicit ratings of items by the user and finding similarity among several like-minded users to recommend an item. Such users build a group of people who have rated same item and have similar taste called neighbourhood. Prediction of target user's rating on a particular item can only be done by analysing the opinion or rating given by the similar user. This technique has two approaches User-based and Item-based.

Knowledge-based recommender systems Model are particularly useful in the context of items in which ratings are not used for the purpose of recommendation. Sometimes it is hard to fully capture user interest with past data or ratings where user preferences show a subsequent evolution. Here, recommendation process is performed on the basis of similarities between constraints specifying customer requirements and item descriptions[4].

Recommender system classification hierarchy: Context Aware recommendation, takes as inputs contextual profiles of the user and the current context of the target user to compute a list of contextual recommendations. Users' browsing behaviour extracted from the log files[5]. Social recommendation system is the key factor of successful online Sites such as Amazon.com, Flipkart.com, and Netflix as they help users to go through a site and find relevant item[6].

Content based and Collaborative recommendation has already been discussed in the previous section.

Web-based recommendation systems totally rely on social trust relationships between users which indicate similarity of their needs and opinions. Trust can be used to make recommendations on the web because it enables the clustering of users with aggregation of knowledge and credibility[7].

Group Recommender system is designed to make recommendations for group of users In order to perform effective recommendations for a group the system must satisfy the individual preferences of the intended group's members[8].

Demographic recommendation systems based on the demographic profile of the user. Here idea id to suggest items in more powerful personalized way i.e. age, language, sex and country etc[4].

Table-1: Comparison of different filtering approaches.

Filtering Approach	Recommender System Types	Techniques used (Ratings/Recommendations	Merits	Demerits	Existing Application Domains
Content-Based Approach (CB)	News recommendation system e-commerce RS Music RS Video RS Social Tagging Recommender Systems[9]	• User Neighbourhood group are built and top N recommendation are computed. • Similarity can be calculated using Pearson or Cosine measures • TF-IDF measures	• Easy to implement • Descriptive knowledge of item is required • New data can be easily added	• New user problem • Stability problem • Recommendation quality depends on large dataset	• Social Network • Music • E-commerce • E-library • Videos • Newspaper • Web Pages
Collaborative Filtering Approach (CF)	Web based Recommender system[7] Group Recommender system[8]	• Similarity can be calculated using Pearson or Cosine measures • Bayesian belief nets, Clustering, MF algorithm can be modelled dimensionality reduction using SVD, PCA	• Robust in nature • Dynamic Feature improvement through implicit • Improved Predictions performance • Easy to understand	• New user problem • New item problem • Sparsity problem • Expensive model building • Important information is lost due to dimensionality reduction	• Social Network • Audio CD • Movie • Music • E-commerce • E-library • Videos • Newspaper • Research paper
Hybrid Filtering	Context-based recommender system[5] Knowledge based RS[4]	Hybrid CF combining memory based and model based CF algorithms Predictions of both the Approaches can be Merged at the end	• Understands the sparsity, scalability and other problems • Better forecast Performance	• Implementation is costly and increased complexity • External information are needed which are unavailable	• Social Network • Music • Movies • Research Paper • Newspaper • E-commerce • E-library • Videos

Comparison and Interpretation

Content-based techniques totally rely on the descriptive data available for an item which leads it to a start-up problem. CB filtering makes recommendations based on user behaviours in the past. CB systems are exclusively associated with the features and description of the item.

Collaborative filtering technique or system mainly suffers from the overlap in ratings given by few users, those have rated the same item. This problem can be reduced in model-based approach of collaborative filtering where SVD can reduce the dimensionality in the space[10].

Second, a new item with less rating can't be participated in recommendation. Third, accumulation of a new user with few ratings is difficult.

Collaborative filtering is best suited for small sets of data with high density of user interest. Overlap of rating with other user will be less if set of items is large and density of user interest is low. For the dynamic datasets, old ratings will be of no use for new users. CF works best for a user that attempts to categorize it into neighbours of similar taste.

Hybrid recommendations can be done in several ways to gain more advantages. First, in weighted hybridization predictions of both the combined approaches are displayed to the user. Second, switching hybrid has the ability to recommend items that are semantically highly rated but are still relevant i.e. cross-genre recommendation is possible but switching criteria introduce extra complexity.

Third, Feature Combination hybridization adds all the available features extracted from the techniques for recommendation.

Fourth, a staged process can be employed by using one technique to produce candidate set and several technique refine among the candidate set to recommend.

Fifth, feature augmentation is useful in text data, news filtering, book recommendation[7]. Hybridization is actually used to alleviate some of the problems associated with different recommendation techniques.

A systematic qualitative survey has been done with 249 references considering factors like number of recent citations and importance of journal in which the paper has been published[1]. We categorized the research context in seven different parts to find out the count.

From the Table-2 that provides publication statistics upon the work areas done in the research field of recommender system design reveals that although survey on different types of data has already been started in decade of nineties but evaluation part was still need to be evolved. In the late 90's, newer evaluation metrics has been evolved that helped the recommender system designer to evaluate the quality and performance of the system.

Table-2: Publication statistics of RS.

RS Research Context	Publication Count	Year Span
Data-type	18	1995-2012
Survey	12	1995-2015
Information filtering (User Ratings)	14	2002-2013
Recommendation / Ranking Models	19	2002-2014
Evaluation Metrics	09	2005-2016
Performance Metrics	09	2005-2016
Application Domains	17	2002-2015

Conclusion

Recommender systems have their advantages and disadvantages in performing their job. Most of the limitations in each one of the approaches can be complimented by the other. A good recommender system should be able to provide positive and relevant recommendations from time to time and also provide alternative recommendations to break the fatigue of the users seeing the same items in the recommendation list. There will be need of effective evaluation metrics for evaluating the performance of the recommender system. Most of the publications have been done in the context of Data-type, Survey, Applications domains.

Future research frontiers: All existing recommender systems: content-based, collaborative, hybrid, have saved the time of searching and opened new options of filtering information. A survey of these techniques shows that they have complementary advantages and disadvantages. The input dataset is the prominent field for any recommendation system. Dynamic datasets, multi-criteria input, multi-lingual input are very promising approach[11]. We can add pedagogical reasoning methods into collaborative filtering approach. Many potential characteristics i.e. facial expressions, caring, gestures and humours need to be examined in future recommendation system[12]. Social wisdom, explicit friendship strength and mutual trust relations among users can be modelled to improve the quality of recommendation system. The standard way to measure the quality of RS is to have a general framework for standardizing the method and algorithms employed by RS using efficiency and accuracy evaluation metrics.

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