Recommender System for Retail Domain: An Insight on Techniques and Evaluations

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ABSTRACT
Recommender system has been developed as a useful tool especially when we reached the era of big data and in the meanwhile the internet has been overwhelming with lots of choices. There is a need for people to filter the information to search for their needs and wants efficiently. E-commerce website such as Amazon and Netflix have been using recommender system to build and boost their sales through the personalization recommendation. With the success in the e-commerce area, researchers are keen on finding a method to boost traditional offline retailer sales thru the recommender system. Therefore, in this paper, we introduced the existing recommender system and discuss the method of filtering of each method. Then, we provide the overview of the recent paper in retailer and e-commerce domain to provide the insight and trends such as the filtering techniques and evaluation metric used. Several possible research direction has been discussed based on the current trends and problems.

CCS Concepts
• **Information systems→Information retrieval→Retrieval tasks and goals→Recommender systems.**

Keywords
Recommender system; Content-based filtering; Collaborative filtering; Hybrid filtering

1. INTRODUCTION
Recommender System (RS) is a system that intelligently provides recommender lists to user according to their interests. With numerous amount of data flow over the internet nowadays, user may find it difficult to search for the actual information that they needed. With the existence of RS, user can get customized recommendations based on their input including user rating, preferred category, search results and so on. Some e-commence company such as Amazon [1] and eBay [2] have integrated the RS into their website to promote targeted products to the customer based on their interest. A high quality RS can improve the user experience as well as improve the sales of the company [3].

The RS approach can be mainly classified into content-based filtering (CB) and collaborative filtering (CF). In general, a CB RS takes user preferences and history details, then provide the recommendation that matches with the preferences and history. CF RS provides the recommendation based on the previous user that having similar preferences and history. On the other hand, more recently, another group of RS namely, hybrid RS has emerged. Hybrid method basically overcomes the limitations of one approach, by combining the good features of the other approaches. There are also knowledge-based RS which recommend items based on the domain knowledge.

The first RS was developed by Goldberg, Nichols, Oki & Terry in 1992 [4]. Tapestry was an electronic messaging system, in which allowed the user to filter and rate the message. RS has been proven that it provide better results compare to simple filtering technique [3, 5, 6]. Real world application like Amazon [1] using item to item collaborative filtering techniques to recommend the same types of item to the same group of users. Movielens [5] recommends the movies based on the collaborative filtering, which utilizes the rating to search for similar user profile. Netflix [6] uses matrix factorization method to adapt the changing of user preference over time in the model.

Recently, many researchers have enhanced the RS and apply in many domain such as e-commence [7, 8], video [9], tourism [10], books [11] and social media [12]. The enhancements include optimizing the RS structure, algorithms and techniques. In this paper, we focus on discussing RS in retailer domain (which includes offline shops and online shops (e-commerce)) from year 2017 to 2019. We will provide an overview of the method of RS used and evaluation techniques for the RS.

2. RECOMMENDATION TECHNIQUES OVERVIEW
Many recommendation techniques have emerged since the inception of RS. These can be grouped into CB, CF and hybrid filtering. There are also other categories such as graph-based, deep-learning based, knowledge-based and so on. We will briefly describe these techniques in this section.

2.1 Collaborative Filtering-Based Recommendation Techniques
In CF techniques, it finds the similar user and use the similar user's preferences or rating pattern to produce recommendation. This approach has been widely adopted in various domains. CF techniques can be further classified as memory-based and model-based. The memory-based system takes user and item relationship into consideration to find the similar user and items. The memory-

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based can be further classified into user-based approach and item-based approach. User-based approach chooses the similar user based on the similarity metrics between users, while item-based approach identifies the user items and compute the predictions based on the similarity metrics between items.

On the other hand, the model-based uses the training data to train the model. The model will be applied to provide recommendation once it is trained with proper data. The training process takes most of the time to learn the pattern.

In general, CF suffers from cold start problem and data sparsity problems. Cold start problems occur when the number of user in the system is not enough to predict the similarity user profile. Data sparsity means that user only rate few of the items, which is hard to predict user preferences.

2.2 Content-Based Recommendation Techniques

CB recommends items based on user profile such as user preferences or user's historical data to suggest the similar items to the specific user. This technique is useful in text-intensive areas, which keyword will be used as content. According to a survey by Beel et al. [13], 55% of the research papers from year 1998 to 2016 touches on the content-based recommendation techniques.

Contrast to CF, CB capable to suggest new item to user. CF is unable to suggest new item where rating is not available yet. Unlike require item rating as a similarity metric which normally cannot get in new item. CB tends to give more personalized data. However, this resulted CB suffers from overspecialization problem, which subsequently spike off many new researchers trying to solve the problem.

2.3 Knowledge-Based Recommendation Techniques

The knowledge-based recommendation techniques recommend items based on the domain knowledge [14]. There are basically three type of knowledge, knowledge about user, knowledge about items and knowledge about relation between user and item [15]. To achieve this, a popular approach which is ontology-based approach has been widely adopted in many research papers [11, 12, 16, 17]. Ontologies are used to model the user profile, item data, and relationship between it. The hierarchical structure allows user to analyze the data at different abstraction levels. Ontology-based recommender approach overcomes the problems such as cold-start, rating sparsity and overspecialization due to the fact that ontology-based recommenders using domain knowledge rather than user rating [11]. The domain ontologies are use to calculate the semantic similarity between items and user. Ontology structure has been constructed in different aspect [18], it helps to provide a common and shared structure, terminology and semantics for the item representation.

2.4 Hybrid Recommendation Techniques

Hybrid recommender techniques combine two or more techniques in generating the recommendation. It used to overcome the issue cause by the specific technique to another such as cold start and over specification [14]. It has been proven increasing the performance of the RS. However, choosing the proper techniques to combine could be a headache. A good combination will have better accuracy of the recommendation whereas a bad combination will cause the performance of the recommendation drops.

Table 1 shows the advantages and disadvantages of each techniques. None of the techniques is perfect as we can notice that each technique has their own advantages and disadvantages. Thus, choosing the correct techniques is important.

Table 1. Comparison between different techniques

Techniques	Advantages	Disadvantages
Collaborative filtering-based	No domain knowledge required. Better result when having huge amount of data.	Cold start problems. Sparsity problems.
Content-Based	Do not rely on user profile. Quality of system improves over a time. No item cold-start.	Overspecialization. User cold start problems.
Hybrid-Based	Overcome some of the issues cause by general techniques. Performance is better.	Need to have knowledge of using correct techniques for a particular domain
Knowledge-based	No cold-start problem. User ratings not required	Need of knowledge acquisition. Static recommendations.

3. RECOMMENDER SYSTEM IN RETAILER DOMAIN OR E-COMMERCE

In this section, we will discuss the papers that were published from year 2017 to year 2019. We will discuss the recommendation techniques used in the system and provide analysis about these papers. Most of the paper focus on enhancing the current techniques such as constructs ontology for the data, combine information of customer review instead of just using product rating and so on.

One of the enhancing methods for CB filtering is to use the details of the customer review. By analyzing the user review, system is able to extract and build the user preferences model [19, 20]. For example, topic modelling method such as Latent Dirichlet allocation (LDA) can be used to derive features in the customer review [21]. Besides, we can also make use of other sentiment analysis methods such as Natural Language Toolkit (NLTK) and part-of-speech (POS) tagging [22]. The NLTK and POS helps to identify, or finding entity or category in the review.

Having a good data structure do helps in increasing the performance of the RS. By constructing an ontology-based system, the data is processed and organize into hierarchy level [23-26]. Customer and products are presented in nodes and relation between them as edges. The relation between each nodes can be easily derive from the structure.

Offline physical shop products usually do not have product rating. This make the general collaborating filtering method lost the feedback input to cluster the customer and item. To overcome the situation, user purchase history can be used as an implicit feedback [7, 27-32]. We can derive the customer purchase history and cluster the customer based on pattern or product category. Customer movement detection such as time in front of products and usually visited area can also act as a feedback to CF [29].

For online e-commerce shops, the product rating is present, but normally sparse and having cold start problem. By adding user browsing history and click streaming, combine with the rating, it can provide much more feedback rather than just using product ratings [7, 8, 29, 30, 33].

To improve the performance of the CF RS, choosing and fine-tuning the clustering method is important. The general clustering method such as calculating the similarity of the item and user by using matrix is not efficient and computationally expensive. Modification to the clustering method can be done in mapping the out-of-stock items to other similar product to improve the coverage at no accuracy cost by favoring less popular items [34]. Another optimization algorithm such as cultural algorithm, a knowledge-based evolutionary optimization algorithm can be applied [35]. Singular Value Decomposition (SVD) can be used to reduce the dimensions of the matrix thus reducing the computational time and data sparsity problems. Another method to reduce the dimensionality is to apply principal component analysis (PCA) [36]. It is a statistical process that transforms the large dataset into smaller dataset without loosing much information. Filtering out fake account and rating will be a good idea in clustering the customers [37]. Accounts that usually have high rating or low rating towards specific brands or categories, will affect the clustering results.

Another method to increase the performance of the RS is to consider the sequence and pattern of the purchase history of customer [23, 31, 32]. With the sequence and pattern of the purchase history, we can gather the information or products that normally will buy together by specific group of people. Sequence mining algorithm can be used to find the sequence items and suggest item to customer [31, 32]. Some system has implemented a preference decay function to reflect changes in preferences over time [7].

Model-based CF techniques based on probabilistic model can be enhancing by using the improved Naive Bayes algorithm, which is Naive Bayes algorithm with bigram language model to improve search query analysis [38]. Association Rule Mining, Bayesian Probabilistic Ranking and factorized personalized Markov chains can also be used to improve the results.

A hybrid system that can detect the situation such as user cold start or item cold start and apply suitable algorithm is needed in order to achieve good result [24, 39, 40]. As we know, most algorithms cannot handle multiple scenario in one algorithm. Different algorithm and techniques need to apply based on the situation to overcome the shortcoming of each algorithm. A hybrid system is not only combining content-based filtering algorithm and CF algorithm, but also combining two CF algorithms are consider as a hybrid system.

Table 2. Recommendation Techniques and its associated publications

Recommendation Techniques	Publication
Content-Based Filtering	[8, 19, 20, 21, 26]
Collaborative Filtering	[27-32, 37,38]
Hybrid Filtering	[7, 22-25, 33-36, 39, 40]

From Table 2, we observed that the CB has the least number of publications. It may be due to the fact that CB has limited information to process the data. Current trends show that more researchers are looking into enhancing the CF or apply two or more methods in the hybrid filtering method.

4. EVALUATION METRICS

Evaluation metrics is needed when we want to know how the proposed algorithm or method performs. It can be used to compare the performance of the proposed algorithm with the baseline algorithm. Table 3 shows the summary of the evaluation techniques used in the paper. We will briefly introduce the top 4 most used techniques.

Table 3. Evaluation techniques and its associated publications

Evaluation Techniques	Publication
Accuracy	[21, 23, 32]
F1-Score	[20, 31, 33, 38, 39]
Precision	[20, 25, 31, 33, 35, 38, 39]
Recall	[20, 21, 24, 25, 31, 33, 35, 38, 39]

Recall, sometime knows as true positive rate, which indicate how many was correctly classified as positive across all the positive data. The higher the recall rate, the better the algorithm (see E1).

$$Recall = \frac{TP}{TP+FN} \qquad \text{E1}$$

TP: True Positive, correctly classified positive items

FN: False Negative, wrongly classified negative items

Precision indicate that how many was correctly classified as positive across all the classified positive data. The higher the precision, the better the algorithm (see E2).

$$Precision = \frac{TP}{TP+FP} \qquad \text{E2}$$

FP: False Positive, wrongly classified positive items

F1-Score, also knows as F-score or F-measure, is the harmonic mean of precision and recall, often used when we need the balance between recall and precision when there is an uneven distributed data (See E3).

$$\text{F1-Score} = \frac{2(Precision \times Recall)}{Precision + Recall} \qquad \text{E3}$$

Accuracy indicate that how often is the classified result are correct across all the data. The higher the accuracy, the better the algorithm (see E4).

$$Accuracy = \frac{TP+TN}{Total} \qquad \text{E4}$$

TN: True Negative, correctly classified negative items

5. DISCUSSION AND RECOMMENDATION FOR POTENTIAL FUTURE WORK

In this paper, we have provided some insight of the RS since year 2017. From Table 2, we can notice that more and more researcher are moving from content-based filtering to CF and hybrid filtering. The reason may due to the CF having better performance compare to just using content-based filtering, while hybrid filtering method overcoming the issue causes by single filtering method thus having better performance compare to other recommendation algorithm.

First, using semantic ways to build a customer and product profile. Traditional way to store and retrieve the massive data take times and hard to maintain. Several methods can be considered such as building an ontological-based customer and product profile. The ontological profile has a hierarchy relationship which helps to organize the data in a systematic way and easy to interpret. The relationship between customer and product can be easily determined by the connected edges without the necessary to retrieve irrelevant data. This helps to reduce the computational power and time. Besides, to form the hierarchy structure, certain data pre-processing need to be done to ensure the data inserted is matching the structure. This helps to organize the data in a more systematic way, and the system can be more scalable.

Second, to solve the shortcoming of the specific RS algorithms, we need to implement a system that can take care of these situations. For example, cold start, data sparsity and etc. The system may need several algorithm to handle different situation, thus a hybrid RS is suggested. We consider that any system that using two or more algorithm is a hybrid RS. However, combining the correct algorithm is a challenge. Throughout the years, hybrid system has shown the capability to solve the shortcoming of different method provided achieving good results in different situation. For example, we may use the content-base algorithm to recommend the products when facing user cold start problem as the user do not have any rating feedback regarding the products. When time goes on, the system will gather enough feedback and we may start using the collaborative algorithm. To deal with the data sparsity problem, SVD and PCA can be used when constructing the matrix used for clustering. We can fine-tune the SVD and PCA algorithms depend on our dataset structure to make it performs better.

Lastly, as we are in the retailer and e-commerce domain, we have to focus on the particular terms such as no product rating for offline retailer, seasonal products and no stock situation. Previous works has shown that the user purchase history can be used to interpret as user preferences and user feedback to overcome the no rating problem. Not only this, the user purchase history and item browse history can be combined with the online product rating to produce more accurate suggestion. The system should be able to handle seasonal product. For example, product such as Christmas tree will only be sold on specific day. Customer preference decay function should also be implemented to reflect changes of customer preferences from time to time.

6. CONCLUSION

RS plays a big role in retailer sector. It helps to boost the income of the company and improve user shopping experience. RS helps user to get interested item intelligently from massive of data. User can get the promotion based on the user preferences or from the same group of people which having some contrast with each other. There are many researchers working on creating more intelligent and high performance RS. In this paper, we have provided several insights such as the overview of the RS and the techniques and evaluation metrics used in recent retailer and e-commerce domain RS.

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