

Research Advanced in the Recommendation Algorithms

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Abstract. In this era of explosive growth of information resources, how to efficiently access the needed resources has become a problem for people. In response to the above practical application requirements, the recommendation system has gradually become a new research hotspot, whose basic task to provide users with efficient and accurate recommendations by modeling the historical behavior of users. In this paper, based on detailed literature research and analysis, we present a comprehensive review of the research work on recommendation technology. Specifically, we summarize three representative methods of recommender systems according to different design ideas, which mainly includes collaborative filtering recommendation algorithm, deep learning recommendation algorithm, and cross-domain recommendation algorithm. Then we analyze the respective advantages of different algorithms and give an outlook on the future research directions of recommendation system.

Keywords: Recommendation Algorithms, Collaborative Filtering, Deep Learning, Cross-domain Recommendations.

1. Introduction

In recent years, the Internet industry has developed rapidly, and while users are able to obtain a large amount of information resources quickly, they also need to distinguish and extract the massive amount of information. At this time, how to find the information resources that users need from the huge amount of information resources has become one of the problems that researchers are currently concerned about. Recommender systems are a proven solution to this phenomenon.

Recommender systems can effectively filter information to alleviate the problem of "information overload" in the information age [1]. It helps users to get the information they need quickly. The core lies in the recommendation algorithm. At present, recommendation systems have been widely used in many fields, such as video sites, shopping sites, social networks and e-commerce. At the same time, there are many different implementation methods of recommendation algorithms, which can be broadly divided into collaborative filtering algorithms, deep learning algorithms, and cross-domain recommendation algorithms. All of them aim at helping users to accurately retrieve information resources that meet their needs in a reasonable way.

Since the first recommendation algorithm, collaborative filtering, was proposed in 1992, recommendation systems have developed rapidly and become a new research hotspot. Collaborative filtering, also known as social filtering, is centered on calculating the similarity between users or products by analyzing the scoring matrix, and then recommending products for users. There are two main types of this recommendation algorithm: user-based collaborative filtering recommendation algorithm and item-based collaborative filtering recommendation algorithm. The former uses the nearest neighbor technique to find similar users, and then predicts the target user's rating of the item. The latter uses the item perspective to find similar items and predict the target user's rating by other users' historical ratings. Collaborative filtering algorithms do not require information about users or items, but only make recommendations based on users and their interactions with items, which is

simple and effective but faces the problem of sparse data and ignores implicit feedback from users. So, scholars have proposed deep learning algorithms.

Deep learning algorithms can effectively alleviate the problems of collaborative filtering algorithms. It is a machine learning algorithm that can recognize, analyze, and compute, and has been used in many fields, such as face recognition, speech recognition, semantic mining, etc. Deep learning algorithm has very powerful functions, and its advantages are mainly reflected in several aspects, such as nonlinear transformation, deep feature learning, high flexibility and usability. Deep learning can analyze data commonality from multiple dimensions. It can discover the hidden potential characteristics of user behavior and capture the nonlinear relationships between users and users, users and items, and items and items, thus greatly improving system performance. Currently, deep neural networks, recurrent neural networks, convolutional neural networks, and graph neural networks have been tried and applied in the field of recommendation systems. However, the above recommendation algorithms are all based on a single domain, i.e., they provide users with recommendation services in a domain based on their preference characteristics for that domain. In this case, the system will face the cold start problem. To address this problem, scholars have proposed cross-domain recommendation techniques.

Scholars found that there is a strong correlation and dependency between user interest preferences or item features from different platforms [2]. For example, users who like to read emotional novels generally like to watch movies based on this novel and also follow actors related to this movie on social media. The same is true for users who like speculative fiction. Based on this phenomenon, academics have proposed cross-domain recommendation techniques. A large amount of user behavior data is stored in mature domains. By sharing and complementing information resources between domains, the data of target domains can be enriched and the interests and preferences of users in different domains can be integrated to predict user behavior more accurately. There are various mature cross-domain recommendation algorithms, and the above-mentioned collaborative filtering algorithm and deep learning algorithm have been applied in this field.

In this paper, we first summarize the development of recommendation systems based on introducing existing recommendation algorithms. Then we discuss current drawbacks and future directions for recommendation.

2. Traditional recommender systems

Traditional recommender systems have two main branches, content-based and collaborative-filtering. Both of them rely heavily on historical interactions and user or item attribute. Content-based recommender systems guesses the user-preferred features or behavior given the item's feature. Once the system recognizes the user's preference, it then embeds the user in an embedding space using the feature vector generated and recommends to the user according to their likings. But this method is limited to its reliance on the great deal of domain knowledge, and it can only provide suggestions based on the user's current interest, which means that the method's potential to build on the user's existing preferences is limited.

Collaborative filtering is the method that is based on previous interaction between the user and the target items. Data concerning user interactions with target objects will be put into the system, which are typically stored as a matrix. Collaborative filtering can be furthermore categorized into three subcategories. Model-based CF adopts the technique of data mining and machine learning; Memory-based CF uses the nearest neighbor classification method; The third one is a hybrid of the above two, which raps the advantages of memory-based and model-based. However, traditional recommendation systems suffer from data sparsity and cold start problems. Take the problem of cold start as an example: it occurs when a new user receives irrelevant recommendations when he or she has few interactions with the system and it might lead to overfitting when training for a collaborative filtering-based recommendation system, which greatly affects its recommendation accuracy.

In summary, traditional recommender systems have long suffered from data sparsity, hence the emergence of cross-domain recommendation (CDR), which can improve recommendation performance by leveraging relatively dense knowledge in richer domains. In summarizing CDR approach, we categorize them into four major branches: single-targeted, multi-targeted, dual-targeted and multi-targeted.

2.1. Single-Target Cross Domain Recommendation

The model is given a source domain that contains two sets of data: user and item. The data is consisted of explicit feedback, such as rankings and views, and implicit feedback, such as purchasing and clicking histories, and also a target domain with sparse data consisting of a user and item set. The model then makes recommendation based on the two domains overlapping features, users and items. Content-based and feature-based transfer are the two major approaches in single-target CDR. Feature-based transfer adopts methods of machine learning techniques, e.g., multi-task learning, transfer learning [3], enable cross-domain user/project embedding or rating in the form of direct sharing or indirect mapping. Content-based transfer connects the more intense domains by content information, such as attributes [4]. It then shares user or item information across domains.

2.2. Multi-Domain Domain Recommendation

Multi-Domain Recommendation: the model can be considered as a branch under single-target CDR. But different from single-target CDR, the model is given multiple source domain, which includes multiple users and items sets, and then recommend the set of items to particular set of users. Considering the similarity between multi-domain CDR and single-target CDR, the challenges that multi-domain CDR faces is the same as single-target DCR. To address the conventional challenges. Zhang [5] proposed a solution framework adopting multi-domain collaborative filtering concerning the problem of data sparsity. The multi-domain models proposed in [6] employed various techniques, i.e., feature combination, transfer learning, and active learning transfer information from similar users or from the same user across multiple domains.

2.3. Dual-Target CDR

The framework contains two domains, each of the domains includes a user and an item set. While single-target CDR is only able to enhance the accuracy of the recommendation in the target domain while the accuracy of the source domain is not improved, dual-target CDR improves recommendation accuracies in both domain 1 and domain 2 simultaneously. Better representative embeddings of both the user and item is essential to the model, which is similar to the prerequisite of the single-target CDR. Additionally, since dual-target CDR is improving recommendation in both of the domains, a more effective framework is needed so that the target domain won't negatively influence how the source domain would perform. In [7], Zhu designed the DTCDR, which is a dual-target CDR model that utilizes information from various sources such as rankings, comments and user information to make the embeddings more representative. Further, the DTCDR model adopts three different combination strategies to merge embeddings of similar users together and then share them across domains. Similarly, in [8], Liu also uses a fixed combination strategy. Further, in [9], Li and Tuzhilin proposed a new bi-objective framework, DDTCDR, which focuses on the bi-directional potential relationships between users and items and extracts users' preferences by applying potential orthogonal mappings. The embeddings can hence be transferred in DDTCDR with the help of the orthogonal mapping.

2.4. Multi-target CDR

Instead of enhancing two domains in dual-target CDR, multi-target CDR aims to enhance the accuracy of the recommendation in multiple domains at the same time. The essence here is to utilize the knowledge from multiple domains to help achieve a further enhancement in the performance of the recommendation system. Besides to problems faced by single-target and dual-domain CDR,

multi-target CDR needs to avoid transfers across domain that would negatively affect the recommendation accuracy since in a set of domains, there may exist domains that contain data that is more sparser than others. Though the problem of negative transfer is also faced by single-target and dual-target CDR, it would worsen as the time of transfer across domains increase with the increase in the number of domains. By now, there are few solutions [10] on achieving this goal. Cui's framework produces a more informative users and items embeddings among multiple domains with the help of a shared heterogeneous graph. The MDCDR method proposed by Krishnan enhances the accuracy of recommendation of other domains by holding the auxiliary information from a source domain. But the above-mentioned solutions hasn't taken into account of the problem of negative transfer and multi-target CDR is hence still a task that is waiting to be improved in the field of cross domain recommendation.

3. Deep learning based recommender systems

With the recent success of deep learning in several fields, researchers have been striving to improve the performance of recommendation systems by adopting deep learning methods. Among the number of approaches in deep-learning-based recommendation, we will be summarizing some of the most popular approaches currently in the field.

Convolutional neural networks based recommender systems: the algorithm is designed to take inputs such as image, text, audio, video, and assign importance ratings through learning weights and biases to various aspects and objects in the input and differentiate them from one another. The classification process in convolutional neural networks is much less complicated comparing to traditional classification algorithms as the network is able to learn the filters and characteristics on its own. Wang et al. proposed a visual content enhanced POI recommender system to achieve the extraction of image features with the help of CNN.[11]. How the systems work is that it explores the interaction between visual content and latent user and location factor. He et al. proposed a model that focuses on visual ranking by incorporating visual features that are learnt through CNN into matrix factorization and further extended it through considering user's awareness concerning fashion and the visual elements that facilitates users' selection, Lei et al. [12] created a comparative CNN model for image recommendations. The model is composed of two independent CNNs that are capable of image representation learning and user preference learning with the help of MLP. It compares two image, which one of them is preferred by the user and the other one is not. Besides the above CNN models that are focused on image, Van et al. achieved feature extractions of music signals using CNN. Lee et al. [13] proposed the method based on the prominent CNNs model ResNet to extract audio features [14]. By adopting such model, it greatly weakened the problem of cold start especially in the field of audio recommendation.

Recurrent neural networks based recommender system: The model is best fitted for processing sequential data among all the deep-learning based recommender systems. Hence it becomes the optimal choice when dealing with sequential patterns of user behavior and interactions and also side knowledge that is consisted of with sequential data such as text and audio. Wu et al. [15] proposed a session-based RNN recommender system for e-commerce website. The model adopts fundamental RNNs to produce predictions concerning what user will be buying in the future based off of their click history. In order to maximally reduce the cost of computation associated with the model, it retains only a certain amount of the latest states while disintegrating the older ones. By doing so, it maintained the accuracy of prediction while reducing the computation cost. Quadrana et al. designed a RNN that is specific to session-based recommendation [16]. The network is structured hierarchically. It enables the model to process session awareness and make recommendations in the presence of user identifiers.

Different from the situation when utilizing session-based recommender, sequential recommendation is usually utilized when user identifier is present. This system is capable of modeling the changes of user preferences and it is consisted of two networks that act as components to map the

trend of user and item states. The algorithm enables the model to learn to generate the minimal square error between the predicted and actual ratings overtime. By incorporating various attributes, the system makes prediction ratings. Christakopoulou et al. [17] proposed an interactive recommender system. Focusing on the term “interactive, the model aims to improve the two basic duties in interactive recommendation: ask and respond. Using RNNs, the model is able to both predict the what user might be asking based off of her latest activities such as click history and the responses to the predicted questions. Li et al. [18] designed a RNN model for sequential recommendation that concentrates on user behavior. This model is composed of neural item embedding and discriminative behavior learning. Discriminative behavior learning includes both session and preferred behavior learning.

Restricted Boltzmann Machine based Recommendation is yet the first recommender system that is built on neural network. Salakhutdinov et al. [19] first proposed this model and suggested integrating implicit feedback with the help of a conditional RBM. To accommodate the limitation that the visible unit of the RBM is limited to binary values, we use a one-hot vector to represent the rating scores. The central idea is that regardless of how the users rate items, users still give ratings that implies their preferences. Georgiev et al. designed a framework that merges the two RBM-CF. The visible units in this model are now determined by both user and item hidden units.

4. Discussion

With the rapid development of information technology and the Internet industry, information overload has become a huge challenge for information processing, especially for recommendation systems. Although recommendation algorithms have been widely used, there are still some challenges to be solved. In this section, we summarize the problems existing in the recommendation algorithm, and discuss the possible future development directions of the recommendation algorithm in combination with these problems as follows:

4.1. Future research directions for collaborative filtering recommendation

4.1.1. Using graph neural network:

Recently, methods for analyzing graphs with machine learning have received increasing attention due to the powerful expressiveness of graph structures. Graph neural network is a deep learning method that is mainly used to process graph domain information. Currently graph neural networks have become a widely used graph analysis method. The user-item interaction in recommender systems can be viewed as a graph, in which users and items are nodes and interactions are edges. Using a graph can help us turn the large-scale data problem into a large-scale graph problem. And thus, we can solve it by sampling or sub-graph training for optimization.

4.1.2. Using knowledge graph:

In most recommendation scenarios, items might contain abundant knowledge information. Thus, we can use a knowledge graph to characterize the knowledge. Using a knowledge graph can not only help optimize the problem of cold start in recommendation because the knowledge is structured, but also expand the item information and strengthen the connection between the items, providing important reference for recommendation. At the same time, using knowledge graph can bring additional diversity and explanation to the recommendation results. However, most of the existing knowledge graph model structures are static, and in practical application scenarios, knowledge graphs have a certain timeliness. Thus, studying how to characterize the time-evolving network and consider the timing when recommending is a promising future research direction.

4.2. Future research directions for CDR

4.2.1. Heterogeneous cross-domain recommendation:

The premise of most of the existing cross-domain recommendation is that the cross-domain information is homogeneous, but in common practical application scenarios, there exists heterogeneous cross-domain information.

In this case, enhancing the similarity of the information is helpful for us to deal with the heterogeneous cross-domain information we might come across.

A promising aspect for this problem is heterogeneous data transfer:

Different domains have a wealth of different kinds of information. For example, in a music player platform, data types are music playing records and favorites. This is the type of user-item interaction data. However, in a social domain, like WeChat, Instagram or twitter, there are abundant data of user-user interaction data. Therefore, this emphasizes that heterogeneous data transfer is a promising future direction for CDR.

4.2.2. Sequential cross-domain recommendation:

CDR also face the same problem as the traditional recommendation methods do: the sequential recommendation problem. As mentioned in [20], many scholars are studying sequential recommendation because it can recommend items to users by modeling the sequential dependencies of user-item interactions. However, as mentioned in [21], sequential CDR requires not only modeling of sequential user-item interactions but also cross-domain information. This makes it more challenging.

4.2.3. Privacy preserving cross-domain recommendation:

Most approaches to implementing CDR today assume that cross-domain data is provided in clear text, but in some real-world application scenarios, there are data isolation problems. Most of the data contains sensitive information like the user profiles and user's browsing history. For CDR, the information we get usually comes from other platforms. And for the platform that owns the data, they usually wouldn't provide the sensitive information for the CDR in the form of clear text. Instead, the information is more likely to be encoded. Thus, it is imminent to develop a method to do CDR while protecting data privacy. Current research on privacy-preserving CDRs can only deal with simple social matrix decomposition models. Therefore, there is still a long way to go for complex privacy-preserving CDR.

4.3. Other future research directions for recommender systems

Recent researches show that giving reasons for recommendation can make it more acceptable and recognizable for users. Recommendations without explanations are not always convincing for all users. If when recommending virtual items online, we can provide explanations and explain the reason for the recommendation as we do offline, we can improve the transparency of the recommender system and also improve users' trust and acceptance of the recommender system. This in turn increases user satisfaction with the items that we recommend. As mentioned before, using knowledge graphs for recommendation is one way to increase explanation. Also, establishing model-agnostic explainable framework for recommendation is a plausible way.

5. Conclusion

In this paper, we discuss the research progress of recommender system tasks from both traditional and CNN-based recommendation algorithms. For traditional methods, we first introduce the recommendation algorithms based on content and collaborative filtering. Then a variety of different cross-domain recommendations are introduced in terms of single-target CDR, multi-target CDR, dual-target CDR, and multi-target CDR, depending on the cross-domain recommendations. We also

introduce the most popular CNN-based recommendation algorithms. Finally, we discuss around the limitations of current recommendation models and predict future research directions.

References

- [1] Liu J L, Li X G. Technical progress of personalized recommendation system [J]. Computer Science, 2020, 47(07): 47-55.
- [2] LI B, YANG Q, XUE X. Can movies and books collaborate? Cross-domain collaborative filtering for sparsity reduction[c]// Proceedings of the Internet Joint Conference on Artificial Intelligence. USA: DBLP, 2009; 2052-2057.
- [3] Hlomo Berkovsky, Tsvi Kuflik, and Francesco Ricci. "Cross-domain mediation in collaborative filtering". In ICUM, pages 355–359, 2007.
- [4] Guangneng Hu, Yu Zhang, and Qiang Yang. "Transfer meets hybrid: A synthetic approach for cross-domain collaborative filtering with text". In WWW, pages 2822–2829, 2019.
- [5] Yu Zhang, Bin Cao, and Dit-Yan Ye- ung. "Multi-domain collaborative filtering". arXiv preprint arXiv:1203.3535, 2012.
- [6] Orly Moreno, Bracha Shapira, Lior Rokach, and Guy Shani. "Talmud: transfer learning for multiple domains". In CIKM, pages 425–434, 2012.
- [7] Feng Zhu, Chaochao Chen, Yan Wang, Guanfeng Liu, and Xiaolin Zheng. "Dtcd: A framework for dual-target cross-domain recommendation". In CIKM, pages 1533–1542. ACM, 2019.
- [8] Meng Liu, Jianjun Li, Guohui Li, and Peng Pan. "Cross domain recommendation via bi- directional transfer graph collaborative filtering networks". In CIKM, pages 885–894, 2020.
- [9] Pan Li and Alexander Tuzhilin. "Dtdcd: Deep dual transfer cross domain recommendation". In WSDM, pages 331–339, 2020.
- [10] Adit Krishnan, Mahashweta Das, Mangesh Bendre, Hao Yang, and Hari Sundaram. "Transfer learning via contextual invariants for one-to-many cross- domain recommendation". In SIGIR, pages 1081–1090, 2020.
- [11] Suhan Wang, Yilin Wang, Jiliang Tang, Kai Shu, Suhas Ranganath, and Huan Liu. 2017. "What Your Images Reveal: Exploiting Visual Contents for Point-of-Interest Recommendation".
- [12] Ruining He and Julian McAuley. "VBPR: Visual Bayesian Personalized Ranking from Implicit Feedback". In AAAI. 144–150. 2016.
- [13] Aaron Van den Oord, Sander Dieleman, and Benjamin Schrauwen. "Deep content-based music recommendation". In NIPS. 2643–2651. 2013.
- [14] Hanbit Lee, Yeonchan Ahn, Haejun Lee, Seungdo Ha, and Sanggoon Lee. "Quote recommendation in dialogue using deep neural network". In SIGIR. 957–960. 2016.
- [15] Sai Wu, Weichao Ren, Chengchao Yu, Gang Chen, Dongxiang Zhang, and Jingbo Zhu. "Personal recommendation using deep recurrent neural networks in NetEase". In ICDE. 1218–1229. 2016.
- [16] Massimo Quadrant, Alexandros Karatzoglou, Balazs Hidasi, and Paolo Cremonesi. "Personalizing session-based recommendations with hierarchical recurrent neural networks". In Recsys. 130-137. 2017.
- [17] Konstantina Christakopoulou, Alex Beutel, Rui Li, Sagar Jain, and Ed H. Chi. "Q&R: A Two-Stage Approach toward Interactive Recommendation". In SIGKDD. 139–148. 2018.
- [18] Zhi Li, Hongke Zhao, Qi Liu, Zhenya Huang, Tao Mei, and Enhong Chen. "Learning from History and Present: Next-item Recommendation via Discriminatively Exploiting User Behaviors". In SIGKDD. 1734–1743. 2018.
- [19] Ruslan Salakhutdinov, Andriy Mnih, and Geoffrey Hinton. "Restricted Boltzmann machines for collaborative filtering". In ICML. 791–798. 2007.
- [20] Shoujin Wang, Liang Hu, Yan Wang, Longbing Cao, Quan Z. Sheng, and Mehmet Orgun. Sequential recommender systems: challenges, progress and prospects.
- [21] Muyang Ma, Pengjie Ren, Yujie Lin, Zhumin Chen, Jun Ma, and Maarten de Rijke. "-net: A parallel information-sharing network for shared-account cross-domain sequential recommendations. In SIGIR, pages 685–694, 2019.