Research of News Recommendation Algorithms based on Deep Learning

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Abstract. Deep learning is the key development trend of news recommendation technology, which has been thoroughly studied by most researchers. In today's social, news recommendation has become a very essential way for people to acquire news. The fundamental idea and procedure of news modeling are covered in this paper's main body, and one of our research interests is how to leverage convolutional neural networks to create news recommendation technology. We also looked at the news recommendation evaluation index, which looks at things like satisfaction, accuracy, diversity, and innovation. Additionally, this paper analyses numerous traditional algorithms and contrast the benefits and drawbacks of each. We also outlined a number of the challenges that the current study has faced. To contribute to this research, we looked into the expected future evolution of news recommendation technology.

Keywords: News Recommendation Algorithms; Deep Learning; Challenge.

1. Introduction

A good solution to the issue of users receiving pointless information is news suggestion. Users may find it useful in separating the information they are interested in from the volume of news material. In order to deliver individualized suggestions and enhance user experience, prominent news websites and apps like Jinritiao and news websites like Sina have included recommendation algorithms in their websites. For instance, Toutiao developed a news recommendation algorithm based on the features of news content, users, and the environment, and effectively implemented it on their portal websites [1]. News presents challenges in the subtasks of user overall preference modeling, user temporal interest modeling, and news modeling compared to other suggestions like goods, travel, and food because to its strong timeliness, rich information, and various user interests. News recommendation has emerged as a very popular project in recent years, attracting the attention of both domestic and international researchers working in the disciplines of information retrieval, data mining, and artificial intelligence. Network news is becoming the most practical means to get up-to-date information [2]. Users can browse news content on other social media and read the news on specialized news websites (such as Twitter, Weibo, etc.). In order to suit the demands of various users for news information, news suggestion can push news resources that users may be interested in as far as feasible, efficiently filter irrelevant news, and enhance the quality of users' reading. Network communication at the moment is distinguished by extensive communication, great immediacy, vast amounts of information, and flexible engagement. With the explosive growth of news amount, strong news timeliness, rich semantic content, and dynamic changes in user interest, network-based news recommendation faces obstacles.

2. Overview of the News Recommendation System

With the development of the news recommendation system, many methods have been created, some of which are widely used in many online news websites. Generally, the process of the news recommendation system can be illustrated as follows. First, the news recommendation system extracts the information from news using strategies, i.e., feature extracting, and NLP. Then, every reader in the system will generate a personal information matrix according to their clicked history. The news recommendation system will match users' information and the news and select the recommended news by using methods i.e., deep-learning method, And the users' feedback will be tracked, based on which we will evaluate the model and modify the parameters to enhance the performance of the news recommendation system the whole process can be illustrated in figure 1.

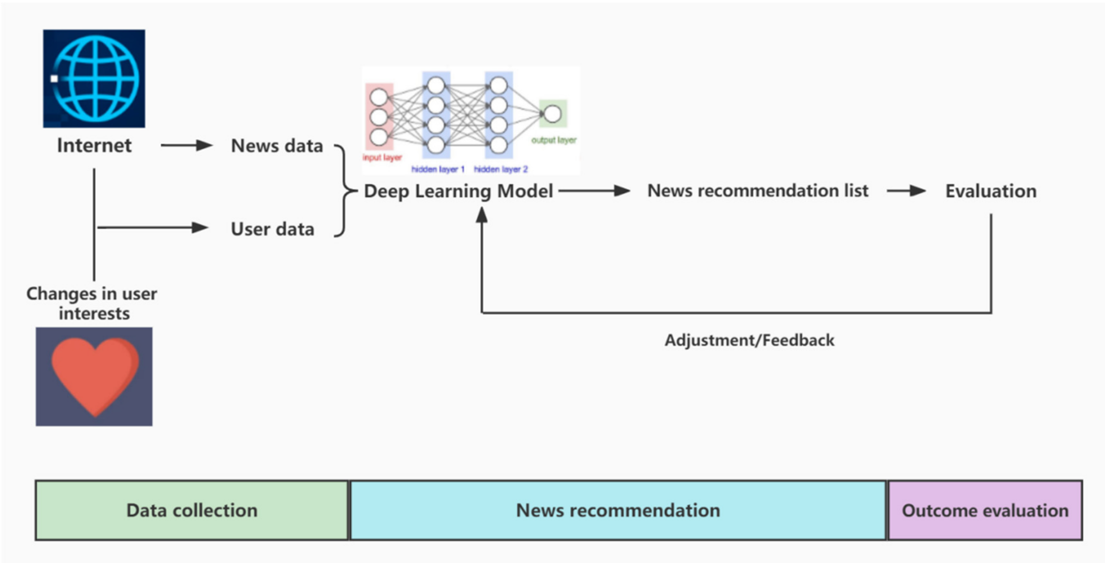

Fig 1. The architecture of the deep-learning based news recommendation system [3]

3. Deep-learning based News Recommendation System

Deep learning-based solutions for news recommendation often integrate deep learning with news recommendation algorithms and employ deep learning technology to extract features from user and news data. This study splits the news recommendation approaches based on deep learning into two categories: Traditional methods, and multi-network fusion methods in order to make the analysis and introduction easier.

3.1 Traditional Methods based on Deep Learning News Recommendation

In Traditional methods, data extraction is the fundamental part of the news recommendation system. How to properly extract information from the news and users' behavior has always been a problem for the researcher. From the perspective of news modeling, a news article has a large amount of information which is hard to extract the key information. From the perspective of user modeling, it is hard to define the user's interest.

Facing these problems, lots of researchers in this field raise their schemes, some of which are widely used in today's news websites, and we will talk about them in the following.

3.1.1 News Modeling

Natural Language Processing (NLP) is a widely used method to extract information from text. Nowadays, the development of the neural network also promotes the development of NLP. And Convolutional Neural Network (CNN) is a typical technique that implements in NLP. CNN convolves the words from news text and uses the pooling method to generate the largest feature. Taking Kim CNN [1] as an example. Every word in the sentences will be changed into a vector and the embedding matrix is the combination of them. Then convolutional operation with filter is then applied to every position in the embedding matrix. A feature map is generated once it has been applied to the embedding matrix. The most significant aspects are then selected from the feature map using a max-over-time pooling procedure, and these features are combined to create the sentence representation.

Inspired by CNN, lots of new ideas have been developed. DKN [2] introduces the Knowledge Graph to CNN and names it a knowledge-aware convolutional neural network (KCNN). KCNN takes the words of the news title as input and searches the related entities in the Knowledge graph. Then the entities matrix will be aligned with the word embedding matrix. The process is illustrated in Figure 2. The researchers also note that the contextual information will help locate the position of the entity in the knowledge graph and improve the identifiability. The implicit relationship between news can be more effectively captured by connecting the news title and entities from the knowledge graph. And the limitation is that it only makes use of the news title and does not make full use of entities with rich semantics in the news context. Based on DKN, Fine-Grained Deep Knowledge-Aware Network uses a self-attention mechanism to build semantic and knowledge-level news representation, and its architecture contains a word-level and item-level self-attention module [4]. The word level self-attention module computes the semantic level and knowledge level representation of news using inputs from news tags, entities in the knowledge map, and their contexts. The specific operation is to select n words as the keywords of each news according to the relevance of tags and news and select key entities and key contexts from the knowledge map through these keywords. To integrate other words and get the word-level representation, it fed the keywords to the self-attention model. The representation of other levels can be generated similarly [5]. The fusion of the three-level representations generates the final news representation, which is more accurate.

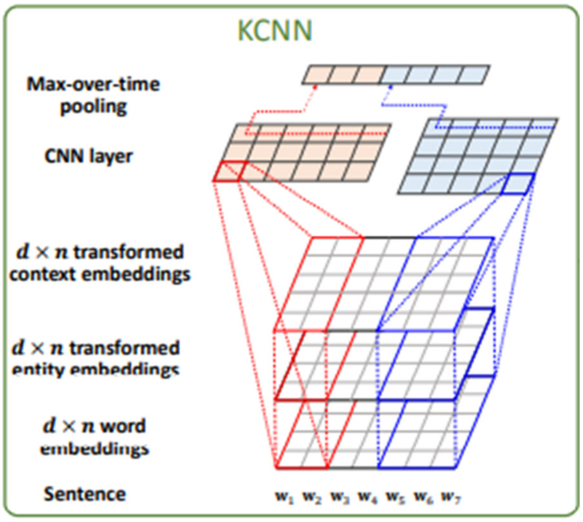

Fig 2. The illustration of KCNN [2]

CNN method can effectively capture the semantic features of news. It has a fast-computing speed and good performance. A lot of related work has been done and there are widely used in news recommendation systems. But the fixed receptive field of CNN may limit the length of news word sequence and influence the accuracy [6].

3.1.2 User Modeling

A critical part of the News recommendation system is user modeling. Based on user modeling, we can forecast the user's preference and propose news stories. Building the user model is a challenging problem because users' interests are always changing and sometimes the scope of interests is very broad. Usually, the preference of users is the modeling of users' long-term interests. Generally speaking, aggregating users' news click history can get users' overall preferences. However, not every news click has the same importance for modeling users' interests. Therefore, many systems use AM mechanism to learn the importance and weight of different news clicks [7]. Taking DKN as an example, the process is shown in Figure 3. Based on obtaining the expression vector of each input news, the attention weight between the candidate news vector and each click news vector is calculated through the AM mechanism. Finally, the weight is dynamically aggregated to calculate the user interest expression from the user's click history as the recommendation basis. NPA (neural news recommendation with personalized attention) model also uses the AM mechanism to model users' preferences, but unlike DKN, its AM query vector is not a candidate news representation but a user's ID embedding [8]. The researcher thinks that the same news has a different amount of information when modeling different users, so the researcher designs a personalized attention network, which gives different weights to the news clicked by the user based on user ID embedding, to obtain the final expression of user interest. In addition to the different importance of paying attention to different news clicked by the same user, there may also be relevance between the historical news, and one piece of news may be related to multiple news articles. Paying attention to the relevance between news articles is also helpful in mining user interests. NRMS uses the multi-head self-attention mechanism in the user encoder to obtain the long-distance relatedness between news to enhance the user's feature expression [9]. Compared with the DKN, the AUC of this model is increased by 4.03%, which improves the ranking ability of the recommendation results of the recommendation model.

This kind of method considers all users' clicked history and emphasizes the different importance of each piece of news. It highlights the key preferences and improves the accuracy of user interest modeling. Because it ignores the impact of the sequence in which people click on the news, this method does have drawbacks. Users' preferences at different time points may be reflected in the order in which users click the news, and finding the relationship among them will help to better model users.

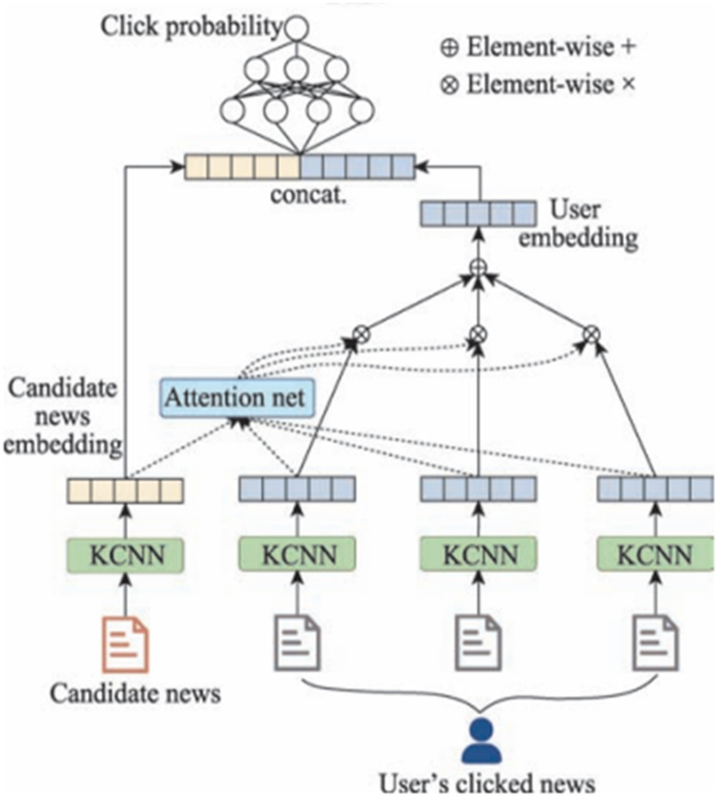

Fig 3. User model of DKN [7]

3.2 Multi-network Fusion Methods based on Deep Learning News Recommendation

In the news recommendation based on deep learning, some methods do not first establish a separate news representation for each article, but fuse news and user information together, and learn news and user characteristics at the same time. This paper summarizes it as a multi-network fusion news recommendation method.

In 2018, the DeepJoNN model proposed by integrates news and user-related multidimensional data (including news categories, keywords and entities, news ID and user ID, etc.) into the same matrix to learn features at the same time [10]. Specifically, the model encodes information such as news categories, keywords, entities, and user IDs as vectors, stacks multiple vectors vertically to form a character-level embedding matrix, and then uses the matrix as the input of CNN to jointly construct news and users, the structure is shown in Figure 4. The model also couples CNN and LSTM in the form of upper and lower layers to simultaneously learn news contextual features and temporal patterns in click streams, and predict the user's next click behavior. Its evaluation indicators R and MRR are both improved on the news dataset Adressa and the music dataset Last.fm, which proves that the model has certain universality. In addition, this model only uses coarse-grained information such as news categories, keywords, and entities, and lacks the mining and utilization of more comprehensive and detailed news semantic information.

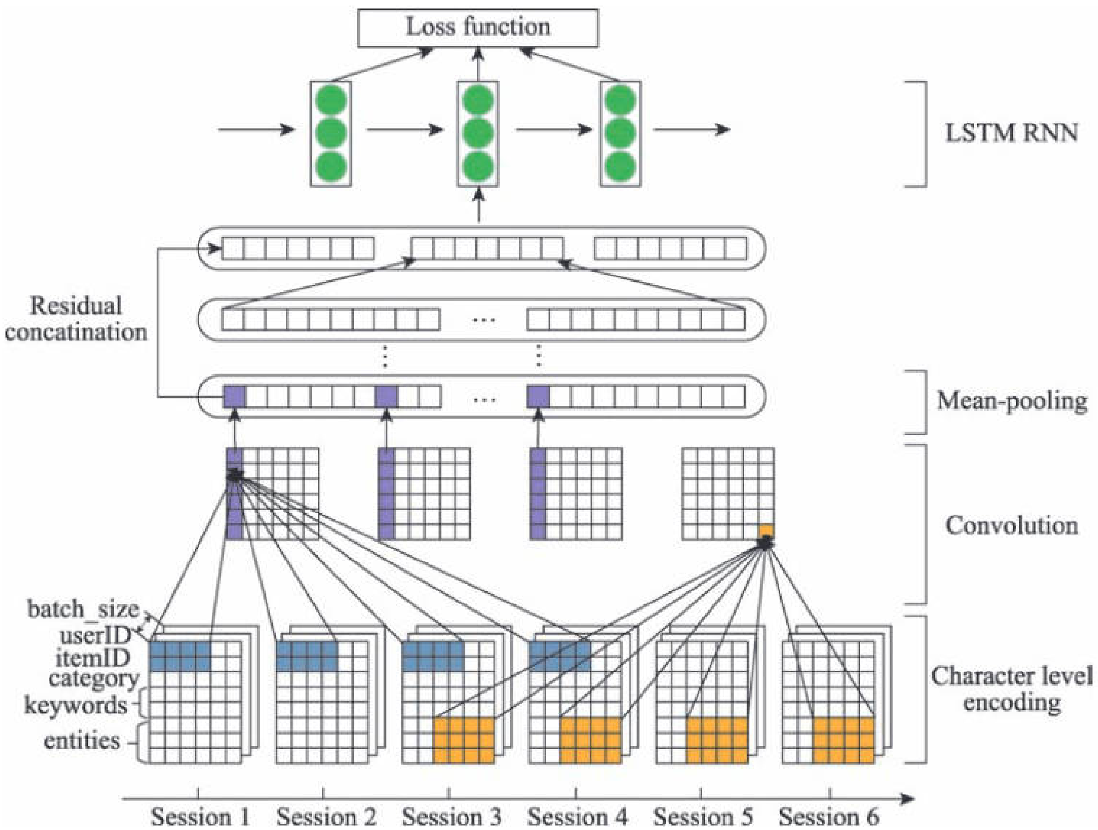

Fig 4. Architecture of DeepJoNN approach [10]

Reference [5] introduced the 3-D CNN (3-D convolutional neural network) model for video action recognition into the news recommendation method, fused user and news information into a 3-D CNN, modeling User time series interest, its structure is shown in Figure 5. The author did not first establish a separate feature vector for each historical news, but with the help of 3-D CNN, the characteristics of the features can be extracted in the two dimensions of time and space through the 3D convolution operation, and the click history of the same user can be merged with the candidate news. Feature analysis is performed in a 3-D CNN network, and a three-dimensional similarity tensor is obtained by calculating the similarity between each word of each article in the user's click history and each word in the candidate news. Based on this similarity tensor, 3D convolution is performed to extract the user's reading interest over time, where the size of the time window for capturing the user's interest history can be determined by the size of the convolution kernel. Overall, the model uses the semantic similarity between words as the input of 3-D CNN to model the user's dynamically changing temporal interest, and the recommendation effect is in the hit ratio (HR) and the normalized discount cumulative benefit (Normalized discounted cumulative gain, NDCG) has improved.

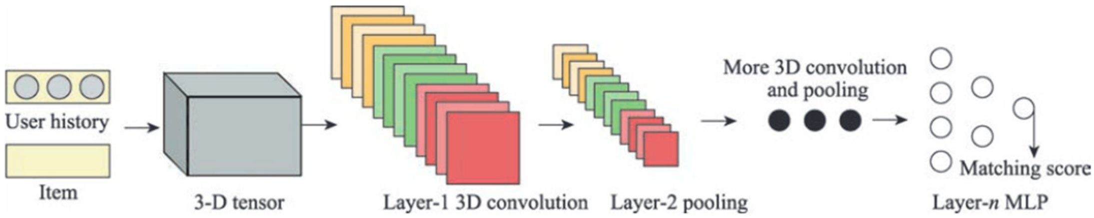

Fig 5. Architecture of 3-D CNN in literature [5]

Reference [6] expands on reference [5] by adding a 2-D CNN (2-dimensional convolutional neural network) and suggests a Weave&Rec framework for news recommendation that models candidate news and user click history independently. In contrast to what was said above, the author immediately employed all of the user's click history as the input of the 3-D CNN and processed alternatively 3D convolution and pooling, where the 3D matrix was concerned. The candidate news is entered into 2-D CNN and processed alternately by 2D convolution and pooling. It is generated by stacking numerous 2D matrices, each of which is made up of the word2vec vector representation of the first 50 words of a clicked historical news. An inner product operation and a fully connected layer compute the final two components of the results to get the anticipated score. The 3-D CNN in this model is able to learn both geographical (news characteristics) and time-series (sequence features in the user's click history) information, capture the dynamic changes in user interests, and ultimately produce higher-quality recommendation effects.

In general, in the "fusion" news recommendation method, each research work mixes news and user information to model, and does not first model each news as a whole vector representation, so there is generally no independent News representation vector. The " fusion" method directly learns news and user features simultaneously on a finer data granularity (such as news categories, content words), making the interests more refined, but compared to the traditional method, it is not clearly defined. The news representation is the same as the user representation, so it is less interpretable, and also has the limitation of lack of novelty in the recommendation results.

4. Performance Evaluation

With the development of recommendation technology and the improvement of data processing capabilities, the current evaluation indicators in the NR field include accuracy, diversity, novelty, and satisfaction. Among them, the accuracy is used to measure the degree to which the recommendation algorithm can accurately predict the user's interest in news, and is the most basic indicator to measure the recommendation algorithm. In fact, since the calculation formulas of diversity and novelty are relatively simple and rough, and satisfaction often needs to be obtained through online user surveys, most of the current research methods aim to improve the accuracy of algorithms.

At present, the commonly used experimental performance evaluation indicators in the NR field include: precision (precision, P), recall (recall, R), harmonic mean F1 of precision and recall, ROC (receiver operating characteristic), area under the curve (AUC), Hit Rate (HR), Mean Reciprocal Rank (MRR), and Normalized Discounted Cumulative Benefit (NDCG). Among them, the accuracy rate P represents the user's click probability on the recommended results; the recall rate R represents the probability that the news that the user is interested in is recommended, which is often negatively correlated with the accuracy rate P; F1 can integrate the accuracy rate P and the recall rate of the recommendation results. R provides a more comprehensive evaluation. AUC represents the extent to which a recommender system can distinguish news that users are interested in from news that are not of interest. It can comprehensively measure the overall performance of the algorithm, and is not only suitable for recommender systems with a clear “like/dislike” evaluation mechanism, and is also suitable for recommender systems without a clear preference threshold (such as a 5-point evaluation). HR@n is used to visually measure whether the test news exists in the top n of the recommendation list. Both MRR and NDCG are indicators to measure the ranking accuracy in the recommendation list. The purpose is to test the user's experience level by examining the ranking position of the recommended results. The difference is that the two are calculated in different ways - MRR is a ranking by accumulating related results. The reciprocal position is obtained, and the NDCG is calculated in the form of log harmonic series. In practical research, in order to analyze the recommendation effect more fairly and effectively, two or more evaluation indicators are usually used to comprehensively analyze the performance of the recommendation algorithm. and NDCG combined evaluation et al.

5. Challenge

Although news information systems have been able to personalize news recommendations based on user interests through different algorithms in recent years. However, there are still some problems with this technology at this stage, and these problems affect the user experience in some aspects. In this chapter, we will introduce the problems in news recommendation systems.

- **Diversity**

Since in news recommendation system, users may be interested in a variety of different topics. Diversity as a key element in the field of news recommendation. Research shows that increasing diversity leads to a better user experience too much homogeneous information will reduce the user's experience. However, among the recent studies on NRS, there are still relatively few studies on the diversity of NRS. Research data shows that most existing news recommendation methods focus only on optimizing the accuracy of the recommendation system, but fail to make sufficiently diverse recommendations. There are approaches that address the diversity issue by recommending news that users have not previously clicked on. But such methods do not balance diversity and accuracy well.

- **Content Moderation**

With the development of social information, the Internet is filled with all kinds of news information. Some of them are false news and even harmful news. This information can have a serious impact on the user experience. In order to avoid spreading this negative information, how to improve the existing news recommendation algorithm is very important. Existing approaches predict whether a candidate news item is false by an RNN-based detection model. There are also methods that analyze the content of fake news by a GRU-based model, and the relationship between the author's topic as a way to make a judgment. However, since the elements for detecting fake news are usually inadequate, these methods are not accurate for fake news.

- **Fairness**

Providing fair news recommendation to users is an indispensable issue in the field of NRS. This means that we need to provide relatively fair recommendations for different user groups. However, existing algorithms often fail to address bias due to gender or occupation. This leads to these users not getting the right recommendations.

6. Future Work

After reviewing some of the current challenges of news recommendation systems, we can see that there is still room for optimization of news information systems. In this section, some important research areas and some possible topics in this field will be discussed in the coming period.

- **User Modeling**

An accurate user modeling is the key to understanding user news recommendations. In order to be more accurate and find the user interest, finding a more accurate user model has been a research hotspot. Most of the existing news recommendation systems tend to use the user's click history as a reference standard, but due to the possible randomness of click behavior, it is obviously not enough to use this as a standard. In addition to the user's click history, the user's other behavior should also be included in the reference standard. For example, the user's web browsing history and user behavior can help us to better understand the user's interests.

- **Deep neural recommenders**

With the rapid development of DL methods, traditional recommendation algorithms are still in need of improvement for existing news recommendation methods. News recommendation systems can produce more powerful and efficient models by combining a wide variety of other neural networks up. For example, CNNs can be used to learn feature representations from news content, and these models can also be combined with neural attention grids to recommend news that better matches user preferences.

- **Privacy Protection**

Since news recommendation systems need to collect users' behavioral data for analysis, there is a risk that this method may compromise users' privacy. However, there is still relatively little research in this area. So, it is a very important topic for us to improve the security of existing news recommendation systems.

In addition, as mentioned above, with the rapid development of the Internet, the Internet is also full of various malicious attacks on users and platforms. This may not only degrade the performance of the recommendation system, but also lead to data leakage from users or platforms. Existing research suggests that this information can be protected using encryption techniques.

7. Conclusion

In the recent years, through the continuous update and improvement of NRS, personalized news recommendation system has been able to better recommend appropriate suggestions based on users' interests. In general, this paper discusses, categorizes, and summarizes deep learning-based news recommendation methods. According to the different model approaches, the paper classifies the deep learning-based news recommendation methods into two different categories: traditional methods and multi-network fusion methods, and then discusses the classification and performance evaluation. And then we analyze these two major classes of algorithms and discuss the technical features of each of them. Finally, by analyzing the existing technical achievements, we found that although the existing NRS technology has matured, there are still many problems that need to be improved, so we summarize some problems that still need to be solved and looking ahead to future trends in the field of news recommendation. We hope this paper can promote the development of news recommendation system in the future.

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