The analysis of different authors' views on recommendation systems based on convolutional neural networks

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Abstract. Previous research revealed that the recommendation system could be based on convolutional neural networks to offer users some information which they liked to search for in the future. It is already known that the recommendation system can learn by itself, so this paper assumed that there may be other methods which can be applied to the computer program based on convolutional neural networks. This paper finds and summarizes some authors' opinions on recommendation systems based on convolutional neural networks and summarizes their skills which are used to improve the accuracy. The findings indicated that the recommendation system is feasible and is used in many fields, and it has many functions, like analyzing emotions and summarizing users' features, in addition to that, it can make proper judgements on users' preferences. And the link between users and products is very worthy of being paid attention to, and there is a need to add more reference information to the testing module to make it more accurate, and to recommendation system should not be restricted by the current data set, so there should be other analysis on information such as potential emotions to improve the independence of the recommendation system.

Keywords: recommendation system, CNN, recommendation modules, users' emotions, recommendation accuracy.

1. Introduction

The recommendation system has been promoted a lot in some fields, such as learning recommendations based on convolutional neural networks (CNN) [1], which can make individualized information recommendations for students and recommend relevant knowledge points and catch the important information from users' comments. Some of them took advantage of natural language processing to combine the arts, science, and engineering, and use computer language to illustrate users' feelings, while there are still some questions which should be addressed, including the fact that building a module of users' behaviors in a short term should focus on the recent past behaviors like shortening the data in several-year history traits of what the user looked through into one-month or several-week history trait. This paper analyzes different categories of recommendation systems used by different authors in different domains and the feature of their various applications, explores the performance of the

recommendation system module set up by those authors individually, and points out the advantage of those various recommendation systems with a certain function and the author's comments. This research can make different applications of recommendation systems clearer, making people know which kind of method they should use to design their recommendation systems in a specific field which can have a better impact on users' experience.

2. Classifying different recommendation modules

Regarding setting up different recommendation modules [2], one author believes that the off-line recommendation module consists of a neural matrix completion module and an off-line recommendation service module, and the recommendation algorithm uses the CNN-A algorithm. In terms of the online recommendation module, the author thinks that this module can collect the record of users' online blogs and analyze their behaviors and then makes the online recommendation list and send it to the business database, and last, illustrate it to users through the user interaction module. And this module uses the CNN-TA algorithm as its recommendation algorithm.

The author's comments: a non-functional demand which is not mentioned straightforwardly is easily ignored, but it is the key point. There should be five demands, including the interactive demand used to serve users making them receive information in a better way, the safety demand which protects users' privacy, and the accuracy demand because the accurate information can make users more willing to use the recommendation system, and the expandable demand which can adapt to users' new demand every period of time, and the stability demand which shows the system running very smoothly even in the case of the high throughput.

3. The use of a recommendation system

3.1. The application to news

As for the application of news, one author's opinion is to improve K-means [3] and two news recommendation algorithms based on CNN. In comparison, the two algorithms have an apparent effect on recommendation, but there are still some drawbacks. On the one hand, as for the K-means algorithm, it is unilateral that build users' module only by digging into the browsing history, so there is a need to add some features about the user and make users' similarity be calculated with weighted fusion to improve the users' preference module. On the other hand, the author uses the text categorisation module for the news recommendation system based on CNN to improve the training effect.

The author's comments: the media becomes more and more popular, and the chances are that people are exposed to many kinds of news, so the news recommendation system has practical significance. In addition to that, the time factor should be added to the recommendation system because users' interest varies with time passing, and this solution can catch users' real-time hobbies.

As for the application on news, the other author thinks that it is feasible to create a Point-of-Interests recommendation system [4] about the user's hobby based on detecting current events, combining with the current event, proper time opportunity and the feature of users' hobbies, and get inherent characteristics of POI and information about current events from different time periods of data on social media. Creating a tree convolutional neural network can easily and effectively deal with the information about passage meanings in those grammar trees and that information in a sequence of words. At the same time, make a standard about the POI embedding equipped with time sense to reflect those statistics in different modes into a unified embedded zone through multimode embedded modules to trail and catch information of current events on those social media.

The author's comments: combining current POI embedded vectors with a matrix factorization algorithm to create a current POI recommendation system can make the recommendation system learn about the trend of users' preferences in different time periods. Mixing embedded features of POI current events and POI auxiliary information together to help collaborative filtering recommendation modules know about the connection between each user and the POI can help the recommendation system find the potential hobby of the user. It is significant for deriving features of zones and meanings to unify the

position of POI, the keyword and the time unit, which can calculate the similarity between different classes and objects. The POI recommendation module based on detecting real-time events can re-sort the POI recommendation list when the event happens, which is good for exploring the real-time potential connection between different POIs to offer a more accurate real-time recommendation to users.

3.2. The application of medical care

As for the application of medical care [5], one author's opinion is to compare three control groups and one experimental group. The formers are named Moudle1, Moudle2, and Moudle3. Module 1 is based on CNN with collaborative filtering, Moudle2 is the typical 6-layer CNN, and Moudle3 fills the dimension of CNN. The latter is the CNN which is optimized. And then, add some information about the hospital level and users' demands on doctor's age and other context information to Moudle4. What is more, compare their curves about the loss and accuracy, and the fewer the statistic of loss is, the more accurate the module is. After choosing the best module, optimize it and add a convolutional layer and a pooling layer.

The author's comments: Moudle4 is apparently better than the other 3 modules. Its accuracy, recall and F1 score improved a lot, increasing by more than 20%. And when the iteration approaches 10000, the loss error amount can decrease within 0.119, and the function is nearly convergent, which demonstrates that this module has relatively high recommendation accuracy. The research is mainly about theoretical research on an online professional medical recommendation system based on CNN, and this method transfers the link between the expert's advantages and the patient's problem to a feature label, which is novel.

3.3. Hotel recommendation system with analyzing emotions

As for the hotel recommendation system with analyzing emotions [6], one author's opinion is to make a module illustrating the comment text with a vector matrix and put it into the trained analyzing emotion module. First, divide those words and use the word2vec module producing word vectors and input them to a short-text emotion analyzing module which combines Bi-LSTM with the feature of the output of CNN. And let it classify those comments into a positive kind and a negative kind. LDA extracts topic words from the positive comment group and the negative comment group. Finally, the rate of positive comments, topic words, the positive comment group and the negative comment group are put into the list of hotels.

The author's comments: as for short texts, it is feasible to combine with Bi-LSTM and the feature of the output of CNN, of which the accuracy is higher than other modules. As for long texts, multi-head attention can replace Bi-LSTM, and combining it with CNN can pay attention to different aspects of various words. Besides, the length of a sentence does not have an impact on receiving the meaning of the sentence.

On the other hand, the other author thinks that designing a module to classify emotions. First, make a BERT-CNN-Bi GRU emotion classifying module [7] to mainly solve the lack of the ability of static word vectors to express and the lack of ability of traditional emotion classifying modules to derive emotional features from texts. Using the BERT pre-training module to get dynamic word vectors can not only mix information about positions and parts of speech and so on into word vectors, but also get deeper information about word features, and alleviate the difference about various meanings of words, to make the word vector have more variable features of language meanings. Secondly, the author designs a CNN-Bi GRU-FM(CBF) individualized recommendation system, digging further into users' comments to get that information about features, mixing different vectors through the feature mixing layer, and eventually output the score about the user's forecasting goods.

The author's comments: in comparison, there is a gap of 5% between the eventual effects of the Word2Vec word vector module and Chinese BERT pre-training, therefore, the effect of dynamic word vector is improved more than that of static word vector. In terms of short text classifying, the relationship between the above passage and the following passage is quite important, and although many layers in the BERT pre-training module can get features of that deeper information, it is effective to mix with a

combination of neural network and downstream tasks to derive the meaning of the content and the feature to improve the quality.

3.4. The application for purchasing

As for the application on purchasing [8], one author's opinion is that the recent recommendation system relies too much on the total data set while analyzing the interactive information about users and goods to suppose those goods which users do not like or buy can improve the data set, to build an interactor matrix including users' preference and goods. And based on the product list knowledge graph and graph CNN, add the user knowledge graph. And input information through a knowledge graph and combine it with CNN to raise the accuracy of goods recommendations. In addition to that, the information between users and goods is easily caught, and the user's cold-start problem can be addressed.

The author's comments: a data form with a well-structured knowledge graph can effectively improve the accuracy, and graph CNN fully digs high-order language information of users and products, which is significantly better than only using graph CNN of the product knowledge graph, with the data of AUC of module KGCN increasing up 6.2% and the data of F1 of module KGCN increasing up 7.9%, which proves that the users' information is very essential to the recommendation system.

3.5. The application on IPTV

As for the application on IPTV [9], one author's opinion is that with the rapid development of IPTV users and the internet television industry, there is a common demand for recommending interesting TV programs for cable TV users. To address problems that how to catch the information about the feature of users' interests and the character of programs, and how to make sure the practice of deep module simplifies the time complexity, the IPTV recommendation system based on graph learning can make graph convolution operations come true to get collaborative information, and simplifying the module and another method can raise the efficiency.

The author's comments: it is feasible to put collaborative filtering based on light GCN into the IPTV intelligent recommendation field. And as for the recommendation accuracy, the data of LGN is much higher than other baseline recommendation modules. In the practical application, among 5 lists recommended for users, the top 3 are what users are interested in, which shows that using the graphical approach to build a module can learn more detailed features about data and relational learning so that the accuracy can increase a lot.

3.6. The application for shilling attacks detection

As for the protection of the safety of recommendation systems, authors think that it is important to detect shilling attacks accurately and efficiently [10], and the existing detection method usually relies on some features derived from a certain perspective of deep learning or some professional knowledge, and they think that considering automatically derive features from different perspectives, at the same time introducing the fuzzy decision, a detection method can take effect. First, make three behavior matrices from the rating value, rating preference and rating time of each user, using bicubic interpolation to scale those three matrices to get corresponding dense rating matrices, dense preference matrices and dense time matrices. Second, regard those scale matrices of any perspective from each user as an image, train CNN at three different perspectives and calculate the membership of attacking users from every perspective. At last, introducing a group of hesitant fuzzy to make a comprehensive decision about the testing result from those perspectives, according to which to recognize the attacking user.

The author's comments: use SVM-TIA, CoDetector, CNN-SAD, SDAEs-PCA, CNN-R, CNN-P and CNN-T as comparing methods to assess three evaluating indicators, the accuracy, recall and F1-measure of the database of MovieLens 1M and Amazon, the former contains 1000209 scores and their time of 3952 movie projects from 6040 users, and the latter collects 645072 users' scores and the time on 136785 projects. The threshold of hesitant fuzzy distance decisions depends on the membership of attacking users, and deep learning can distinguish normal users and malicious users according to those derived

feature vectors. And the result illustrates that the three evaluating indicators are better than the other seven comparing methods, getting performances of a higher quality.

3.7. The application of intelligent home theater on demand
As for those drawbacks like cold start, the lack of data, the ambiguity of potential features and the lack of interaction between users and the projects, the author think that improving the ConvMF recommendation algorithm [11] and in the field of intelligent home theater on demand, use intelligent voice interactions and web UI creatively as two interactive interfaces to design a recommendation system about a movie list to satisfy users' demands. First, create a score forecast and create a basic information feature matrix about the user and the movie, and the MFF-CF can mix multi-feature information. Second, when creating the word vector modules, add word vectors in the same corpus as an embedding layer of Text-CNN to increase the accuracy of recommendation systems. Thirdly, given that the difference of initial scores of users affects the procedure of decomposing PMF matrices, introduce the SD-ConvCMF recommendation algorithm based on deep learning, and mix it and the MFF-CF. Lastly, design two interaction modules on voice and web UI to create multi-interaction movie list recommendation systems, at the same time, create modules on collecting movie information, downloading data, the engine dealing with data, and making a list recommendation system through the distributed deployment.

The author's comments: with the complexity of recommendation systems increasing, although average each time of iterating during the procedure of Text-CNN training, the accuracy of forecasting users' scores increases up 2.11% and 3.71% respectively after the embedding layer of ConvMF being improved and the decomposing rating matrices being improved, while the accuracy of improved SD-ConvCMF forecasting increases up 5.43%. Therefore, the improved two embedding layers of Text-CNN networks will derive information which can represent potential features of movies, making some additional improvements in the accuracy of forecasting, and improving the experience of using the intelligent home theater on demand.

4. Conclusion
With information becoming more and more varied, people are exposed to much unnecessary news, the recommendation can choose corresponding information for users. Also, the chances are that users leave their views after looking through the information. Given the diversity of users' comments, the relatively more logical computer program should focus on some potential emotions, and CNN should combine with another method like the attention mechanism to raise the accuracy of the recommendation system. The recommendation system has a profound significance, in that it can be used in many fields and help people filtrate [12] some information that is unnecessary.

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