Research on Optimization of Personalized Dynamic Recommendation System of Knowledge Label Based on Artificial Intelligence Algorithm

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Abstract. With the development of Internet, the appearance of knowledge label technology brings new opportunities for personalized recommendation. Knowledge tag connects users with resources, describes the characteristics of resources and reflects users' interests and preferences, which brings a vital data source for personalized recommendation service. At present, the information resources on the Internet are exploding, which leads to the emergence of "information overload" and other problems. Personalized recommendation technology meets the personalized needs of people's different interests to a certain extent. The appearance of tags enables people to label network resources freely. Knowledge tags connect users with resources, describe the characteristics of resources, reflect users' interests and preferences, and bring vital data sources for personalized recommendation services. However, due to the individuation of knowledge tags, semantic ambiguity exists, which reduces the recommendation accuracy based on knowledge tags, greatly limits the application of tags in recommendation, and the rapid expansion of tagging reduces the recommendation efficiency.

Keywords: artificial intelligence · Knowledge labels · individualization · system optimization

1 Introduction

With the rapid development of Internet, Internet of Things and cloud computing technology, modern society is an information and digital society, with data flooding the whole world. Faced with a large amount of data, users' utilization rate of information is reduced, that is, the problem of information overload arises. Recommendation system is one of the key technologies to effectively solve the problem of information overload. It recommends the information that users are interested in according to their needs. After more than twenty years of development, recommendation system has been widely used in e-commerce, search engine, intelligent education and other fields. With the continuous development of probability statistics, machine learning, artificial intelligence and data mining technology, the technology adopted by recommendation system has evolved

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from traditional recommendation technology such as matrix decomposition and probability matrix decomposition to recommendation technology based on modern artificial intelligence technology. Traditional recommendation systems can be divided into two categories: recommendation systems based on content filtering and recommendation systems based on collaborative filtering. The recommendation system based on content filtering mainly screens or sorts the recommended items through the matching or correlation degree of item features and user features.

2 Literature Review

With the rapid development of the Internet, the Internet has been upgraded from Web1.0 to Web2.0, the Web2.0 system represented by blog, wiki, RSS, SNS, knowledge tag and other technologies has changed from the original top-down Web1.0 system dominated by a few resource controllers to the bottom-down, with the top-down system dominated by the collective wisdom and strength of the majority of users. The knowledge tagging system came into being in this environment. In the user-centered Web2.0 environment, the knowledge tagging system allows any user to annotate the interested network resources without restriction, and all users' annotations are visible to each other. This open and shared mode embodies the people-oriented Web2.0 concept, and it also brings new opportunities for the organization, recommendation and sharing of information resources in the new environment. In a word, the knowledge label system fully explores the enthusiasm of users, makes them participate in the system, exerts the influence of the wisdom contributed by the vast number of users and the group wisdom formed by their contacts, and liberates the potential of users' creation and contribution.

3 Research Methods

3.1 Application of Artificial Intelligence Algorithm Technology

As far as the artificial intelligence algorithm technology itself is concerned, intelligent agent technology is widely used in knowledge tagging, thus laying the technical foundation for interactive and personalized tagging. In the computer system, the features of intelligent agents can enrich the application functions, thus completing the corresponding tasks. Compared with traditional algorithms, artificial intelligence algorithms are more advanced, and have higher quality and efficiency. In the personalized knowledge label of artificial intelligence, grasp the progress and analyze its actual situation, so as to design a learning plan for it and make it more personalized. Through full analysis, the corresponding courses can be set for the label [1, 2].

3.2 Knowledge Labeling and Labeling System

For more and more network information, tags classify resources in the form of keywords, and mark resources from the perspective of personal understanding, which not only enriches the different dimensions of describing resources, but also shows users' interest in resources. Knowledge label is a flexible and open classification method, also known as popular classification or Folksonomy. It is a tool for users to use freely defined keywords for collaborative classification. Users can freely choose corresponding labels to label network resources according to their own needs. Each label is a classification of network resources by users. In this way, network resources are naturally organized into different categories according to different labels, and the same label aggregates similar resources of different users. However, knowledge labels are different from the traditional classification method of directory structure. The labels are parallel, regardless of the hierarchical relationship of network resources. Knowledge tags combine the characteristics of "classification" and "keywords", and have great value for discovering users' potential interests from massive data and recommending personalized services for users. It is found that knowledge labels have the following characteristics:

(1) Freedom. Knowledge labels come from network users, who have complete freedom and autonomy in labeling project resources on the network. Any user can mark the resources he is interested in, provide one or more tags, or just browse other people's tags without marking them [3].
(2) Sharing. For any user, all knowledge tags are shared. Each user can freely view or use the labels marked by other users, and the labels marked by himself can also be viewed or used by other users.
(3) Dynamic update. With the increasing number of users' tagging, there are more and more resource tagging information, and the tagging information of resources is constantly updated and enriched.

3.3 Recommendation System Model Based on Knowledge Tag

In order to solve some existing problems in the tag recommendation system, this paper proposes the following tag-based recommendation system model, as shown in Fig. 1:

The construction of such a tag recommendation system model is mainly based on three considerations: ① The research on tagging semantic topic discovery in the module of tag sorting and recommendation algorithm can solve the problem of tag semantic ambiguity in the traditional tag recommendation system. ② Independent user multi-interest model can build detailed models according to practical application fields and update them in real time. ③ Incorporating the resource score into the model can better describe the quality of the recommended project resources. ④ The independent user tag database is used to store the interactive information between users and tags, and the user interest model database is used to store user interest models, which can sort out the tag information and user interest models offline and improve the efficiency of the system.

As can be seen from Fig. 1, the tag recommendation system model in this paper mainly consists of four parts: man-machine interaction module, preprocessing module,

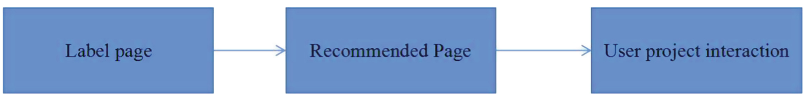

Fig. 1. Recommended system model

recommendation module and system database module. The following briefly introduces each module of the tag recommendation system model:

(1) Human-computer interaction module

Man-machine interaction layer is used to realize the interaction between users and the system, which is mainly divided into three types: user tag interaction interface, user item interaction interface and recommendation result display interface. Among them, the user tag interactive interface is used for users to browse or label resources with tags, and is responsible for receiving data marked or browsed by users and transmitting them to the preprocessing module; The user interaction interface is used for users to score projects, and is responsible for receiving user scoring data; The recommendation display interface receives the recommendation results returned by the recommendation module and displays them [4].

(2) Pretreatment module

The preprocessing module is an intermediate layer, which is responsible for receiving the data transmitted by the human-computer interaction module and performing relevant analysis and preprocessing on the data. It includes three sub-modules: label sorting, semantic topic discovery, and user interest analysis. Among them, semantic topic discovery is one of the focuses of this paper, which can eliminate the semantic problems of labels [5, 6].

(3) Recommendation module

Recommendation module is the core of the whole model, which consists of three parts: user interest model, recommendation algorithm and recommendation result optimization. Among them, the construction of user interest model and recommendation algorithm are also the focus of this paper. Firstly, based on semantic topic discovery, this paper constructs a three-level user multi-interest model to describe users' various interest preferences. Then, combined with the project score, the nearest high-quality project resources are recommended to users by collaborative filtering method. Recommendation optimization is to sort the recommended project resources according to semantic relevance, which is closely related to the recommendation result display interface of human-computer interaction module.

4 Semantic Topic Discovery Method Based on Public Tagging

4.1 Basic Process of Semantic Topic Discovery

The basic idea of semantic topic discovery algorithm based on public tagging is as follows: Aiming at the randomness of tags generated by users of knowledge tagging system, probabilistic latent semantic technology (PLSA) is introduced and extended. The improved PLSA model generates the latent semantics of tags and resources, discovers semantic topics, and eliminates semantic ambiguity problems such as synonym and polysemy of tags; At the same time, the relationship between tags and semantic topics and users' attention to semantic topics are obtained, which provides a good foundation for users to browse, search and recommend in the tag system.

4.2 Tag Clustering Based on Semantic Topics

Applying the improved PLSA model analysis, semantic topics are found, and the distribution of user annotations in each semantic topic is obtained. Clustering knowledge labels into semantic topics can better explain the semantics of labels. For users, a knowledge tag may have multiple semantics, that is, it belongs to multiple semantic topics. According to the correlation between knowledge tags and semantic topics, the method is as follows: input: "knowledge-resource tags" matrix, clustering threshold γ.

The adopted data set is MovieI ens10M100K data set opened by GroupLens Group. Each user in this data set has scored at least 20 movies. As there are as many as 100.000 tag data. There are three DAT files in this dataset: movies.dat, ratings.dat and tags.dat Movies.dat stores the name and movie category corresponding to the ID of the movie, ratings.dat stores the user's rating and rating time of the movie, and tags.dat stores the user's tag information and marking time of the movie. The specific data format is shown in Table 1.

Due to the large amount of data in MovieLens dataset, considering the limitation of experimental hardware environment and time factors, 20% of the data in MovieLens dataset is selected as experimental data in this experiment. Using tags.dat data file, the experimental data is imported into the database, and the UserTags table is generated [7, 8]. A record in the UserTags table represents the record of a specific user tagging a specific movie, and the table definition of the database is shown in Table 2.

According to the method description, the extended PLSA model calculates potential semantics and discovers semantic topics. After many iterations, the objective function values are recorded under different potential semantic space dimensions. For this data, the result is better when the dimension is set to 55. For each semantic topic, the labels

Table 1. Specific data format of Movie Lens10M100k data set

document	format	explain
movies.dat	Movie ID::Title::Genres	Movie ID, name, genre
ratings.dat	UserID::MovieID::R ating::Timestamp	User ID, movie ID, rating, time stamp
tags.dat	UserID::MovieID::Tag::Timestamp	User ID, movie ID, label, time stamp

Table 2. User Tags

field name	type	describe
ID	Char	Primary key, self-increasing ID
USER ID	Char	User ID
Movie ID	Char	Movie ID
Tag	Char	The user's label for the movie.

are arranged from p(z\tn) to the lowest, and the label sets under each semantic topic are recorded, so that the intuitive label representation of the semantic topic can be obtained [9, 10].

5 Conclusion

With the continuous development of artificial intelligence technology, all kinds of things must keep up with the development of the times, and constantly study related technologies to promote the further development of artificial intelligence technology. As the most basic component of knowledge tag system, knowledge tag reflects users' interests. However, due to the semantic fuzziness of tags, the role of tags in recommendation cannot be fully exerted. The discovery of semantic topics reflects the latent semantics behind knowledge tagging, which provides a good semantic foundation for browsing, searching or recommending resources through knowledge tagging.

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