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Application of artificial neural networks on personalized recommendation algorithm

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ABSTRACT

Personalized recommendation aims at providing information and goods according to customers' interests and behavior. The deficits among recommendation algorithm pose challenges to system as its scale accumulates. Therefore, several techniques have been adopted to improve it. This paper will give a brief introduction of the common principles of artificial neural networks and recommendation algorithm and elaborate on the combination of the two.

KEYWORDS

Artificial neural networks; Personalized recommendation; Recommendation algorithm.

INTRODUCTION

1943 saw the first neural math model in world, MP model, proposed by McCulloch and Pitts, who also proved this network could calculate any possible functions. After a long period of stagnancy, ANN embraced its prime time again in 1980s when functional PCs and work station were widely used and concepts were innovated. In 1982, Profession J.Hopfield made breakthrough in ANN field with his Hopfield network.

In 1989, China had its first unofficial ANN conference in Beijing. Two years later, China ANN Associate was founded in Nanjing. Currently, the application of ANN in China evolves industry, transportation, economy, astronomy, agriculture, environment, etc.

PERSONALIZED RECOMMENDATION ALGORITHM

Collaborative Filtering

The 1.0 version, also known as customer-based collaborative filtering[1], this algorism seeks for "nearest neighborhoods", a set of users who have same interests with the target user, thus producing TopN recommendation set.

To overcome the limits of the 1.0 version, item-based 2.0 version came into being, which provides more table item quantity. The comparison of the two versions is in TABLE 1.

TABLE 1: The comparison of two versions of collaborative filtering

Item	Version 1.0	Version 2.0
Complexity	O(m2) m indicates users	O(m*n2) N indicates items
Merits	Considering the group characters among similar users	Stable items quantity and less system calculation
Defects	Cold start and high cost for users' similarity calculation	Data sparseness weakens recommendation accuracy

Limits of Collaborative Filtering

Both Version 1.0 and 2.0 encounter the problem of data sparseness[2]. Since in any given websites, the grading and purchasing records account for very small portion compared with all the available sets, thus it is even harder to find similar user sets when there is few intersections. What's worse, huge amount of data still pose challenge to the calculation complexity, which requires clustering on the grading data.

ANN THEORY MODEL

ANN, artificial neural network, is a network widely connecting a great quantity of processing units. Generally, it possesses 3 essential factors:

A group of synapses or connections. w_{ij} indicates the connection strength between neuron i and neuron j, that is the right value.

(2) Accumulator reflecting the input signals.

(3) An activation function limiting the neuron outputs.

A typical ANN model is in Figure 1.

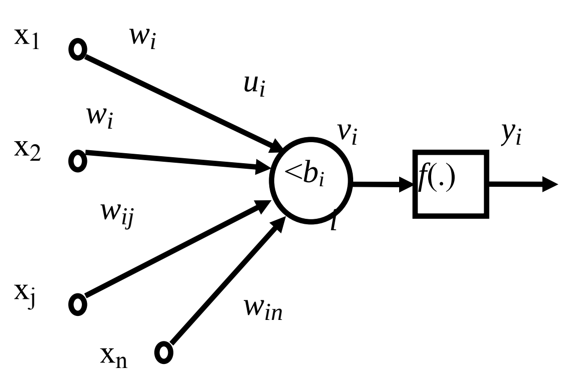

Figure 1 : A typical ANN model

Where x_j (j=1,2,…N) is input signal of neuron i, w_{ij} is the connection strength or the right value. ui is the output of the linear combination of the input signal, the net input of neuron i. bi is the neurons threshold or bias, and vi is adjusted by the deviation of the value.

$u_i = \sum w_{ij} x_j$ (j=1,2,…N, i=j,j+1,…)

$v_i = u_i + b_i$

f(.) is the activation function, yi is the output of neuron i.

$y_i = f(\sum w_{ij} x_j + b_i)$ (j=1,2,…N, i=j,j+1,…)

Threshold function, piecewise linear function and sigmoid function are commonly used activation functions. Hecht, Nielsen defined artificial neural networks as: artificial neural network is the computer system where a number of very simple processing units are connected to each other in some way formed, the system rely on its state of the external input information The dynamic response to process information.

APPLICATION OF ANN IN RECOMMENDATION ALGORITHM

BP ANN Algorithm

BP ANN is back-propagation artificial neural network, thods used in the data analysis were the k-nearest neighbour (k-NN), back-propagation artificial neural network (BP-ANN), FDA, Sammon mapping and the FDA-MSM. This paper creates a linear algebraic equation from the target output given as a linear equation based on Artificial Neural Network; it is not through the inverse transfer function to calculate the net output of neuron. This method simplifies operation steps.

BP learning algorithm is based on the training set automatically reverse the learning of a neural network model. It is divided into the level of the input layer, one or more hidden layer and output layer of three neural networks as in Figure 2.

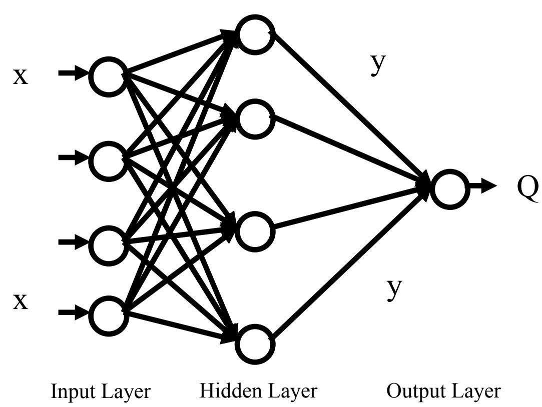

Figure 2: Model of BP ANN algorithm

Each sample contains the input vector and the target output vector. When the sample has been provided to the network, the difference between actual output and the required output is used for the correction weights. The output node has a single input value, the actual output of the error between y and the desired output d is given by (1):

e=d-y (1)

The signal of the output node is x, then need to adjust the volume:

$\Delta W = \eta\delta x$ (2)

Where η is the learning rate, the bigger η value is, the more dramatically power value changes and higher the convergence speed of BP learning. At the same time, change of the volume of the weighted value of the input signal X is proportional to the signal, since the greater the signal, the bigger the correction amount.

δ is the local gradient obtained by the following formula:

$\delta = f'(x)e$ (3)

New weight value is the sum of adjustment value and the old weights:

Wnew = W + ΔW (4)

At the beginning of the training, the weights are small random values. As the training progresses, each sample in turn is transmitted to the network and is constantly modified until any input sample, the difference are within the acceptable error range, or execute a certain number of learning cycle. The learning process is as follows:

(1) Set up network parameters, including the input vector X, the weight vector W, the actual output Y, the desired output d and the learning rate of η, the number of iterations n.

(2) Assign random nonzero value to the weighted value matrix W. Let n = 0.

(3) Input a input vector of a training sample: X.

(4) Calculate the inference output vector: Y.

(5) Calculate error e, then determine whether e meets the requirements, if it is satisfied, go to Step 8; if not, go to Step 6.

(6) Determine whether n +1 is greater than the maximum number of iterations, if yes, go to Step 8; if no, calculate the local gradient δ according to the formula (3).

(7) Calculate weights correction ΔW according to equation (2), and fix the weights. n = n +1. Go to Step 4.

(8) Determine whether a certain number of learning cycle is finished. If yes, End, otherwise go to the Step 3.

BP learning algorithm steps are shown in Figure 3.

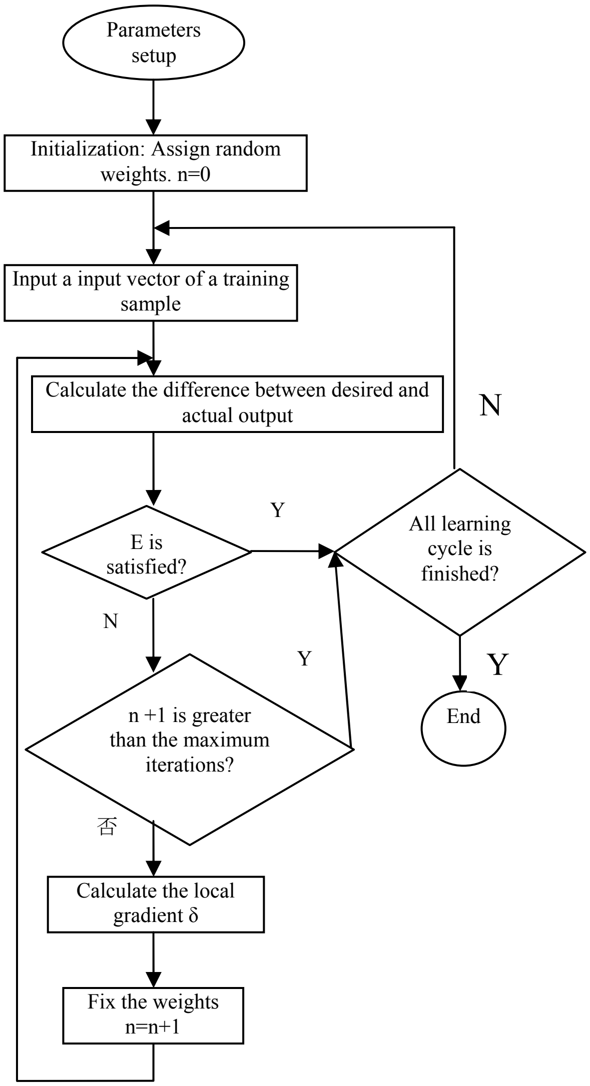

Figure 3: The flow chart of BP learning algorithm

Application of BP ANN in Recommendation Algorithm

BP neural network forecasts the default values to alleviate the sparseness of the set of user ratings, and improve the recommendation quality[3]. Specific steps are as follows:

Data preprocessing

Minnesota State University, Department of Computer Science Research Group to facilitate the personalization algorithm to collect the data set MovieLens[4], the data set contains a total of three sub-sets: the film set of information and data, the project score data sets and user information data sets. Among them, the project score data set contains 100,000 943 users on the 1682 film score record, the rating values are integers from 1 to 5, with higher values, indicating that the users favorite of the film the higher the degree, each The user evaluation at least 20 movies. Select a certain amount (5000 ratings data from the user ratings database contains a total of 152 users and 50 films) score data as the experimental data set, then the experimental data sets are further divided into training and test set, the data set 80% as the training set, 10% as the validation set 10% as a test set.

Establish the neural network

The neural network model consists of many input nodes[5-6], and the i-th input nodes corresponds to i-th item score, m hidden layer neurons and one output contacts constitute, as indicated in Graph 2. Take a three-layer BP network, the main input parameters including the weight vector between the initial value of W1, W2, the error control parameter e and the learning rate η. Activation function to use logical functions[7-9]. For the determination of hidden layer nodes, we use the empirical formula nm=sqrt(ni, no)+1 smallest middle-tier nodes, nm, ni, no are the hidden layer and input layer and output layer nodes. Trial and error method to solve the middle layer nodes, and the last nm value calculated by the general distribution in the [ni, 2 ni].

Training, validating and testing the neural network with validation and test sets to get a more stable network.

Predict

Due to limite space, this data set will be intercepted, through a simplified example to illustrate the BP neural network to predict the null process.

(1) Let optimize computing users - Project score set such as shown in TABLE 2, where uj suggests the j-th user, ii suggests the i-th item, the value within the corresponding table cell is the user ratings.

TABLE 2: User-item ratings set after the optimization of computing

user	**item**					
	i_1	i_2	i_3	i_4	i_5	i_6
u_1	2	3		4		1
u_2	1		2	1	1	3
u_3	4	5	1	5	3	1
u_4	1	2	3		4	1
u_5		2	4	1	5	

(2) To predict the cell value of u1 i5, take out the u1 line, let the rest do the training set, where i5 column is set to be the desired output, the rest are input vectors, the remaining null value is 0. As shown in TABLE 3.

TABLE 3: Ratings set

user	**in**					**out**
	i_1	i_2	i_3	i_4	i_6	i_5
u_2	1	0	2	1	3	1
u_3	4	5	1	5	1	3
u_4	1	2	3	0	1	4
u_5	0	2	4	1	0	5

Conditions determine the neural network has 5 input nodes and one output node. BP neural network is constructed as shown in Figure 4. Training and testing the BP neural network will ensure a stable network structure.

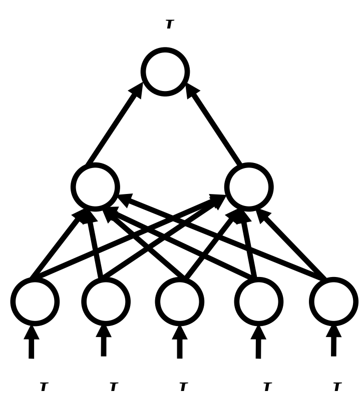

Figure 4: Structure of BP neural network

(3) Input [2, 3, 0, 4, 1] to get u1's rating towards i5.

(4) Repeat similar steps to TABLE 2 and predicted other null values with the neural network training in the above-mentioned process. Until the entire rating matrix sparseness is within a specified limit.

In addition, because the BP neural network realizes a mapping function from input to output, it is used to extract the user's behavioral characteristics and concerns, and establish user interest model to predict the preferences of the users of the project, the resulting recommendation. The experiments show that the BP neural network-based recommendation system, lower than the traditional collaborative filtering algorithm error[10].

Besides, other types of neural networks are also the recommendation system has been varying degrees of application. For example, the clustering characteristics of the ART neural network be used to improve the scalability of the recommendation algorithm. Inhibit the function introduced in the learning process of SOFM neural network to adapt customer scoring the sparseness of the set of neurons in the split-merge process, the dynamic adjustment of customer clustering. Traditional clustering methods to face the dynamic growth of data, lack of robustness and flexibility, based on self-organizing map neural network (SOM) clustering of user information model, and achieved good results in experiments[11-12]. The simple HJ neural network principles can find from collecting information macro separation and user needs information closest to greatly reduce the blindness and inefficiency of the personalized information recommendation, and further enhance the recommendation quality of service.

CONCLUSIONS

The artificial neural network is an emerging area of research, various artificial neural network model is too simple, is far less than intelligent simulation of natural neural networks. Even so, the combinations of model-based artificial neural network with the actual problems have been established. The focus of this study is that the neural network in the personalized recommendation algorithm field, but should see the recommended cold start of the algorithm itself, the data is sparse, and scalability issues still lack a truly effective solution for further improvement. With a variety of neural network model to create a variety of hardware, network equipment, manufacturing process improvement, application of artificial neural networks and related algorithms will be more extensive.

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