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Design and Implementation of Travel System for Disabled People Based on User Interest Preference Recommendation Algorithm

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Abstract: There are a great deal of disabled persons in China's society nowadays, but they often are unable to leave the house because traveling is inconvenient for them. This work develops a recommendation system based on a recommendation algorithm that can assist persons who have disabilities navigate normally. The application of recommendation system technology can help customers rapidly identify the products they're interested in, save time, and assist companies to cut expenses. It additionally has the ability to predict users' ratings or preferences for items. In today's big data environment, there are countless recommendation systems or software for all kinds of commodities. However, giving recommendations for traveling to specific groups of people, including those who are disabled, is uncommon. In order to meet the needs of people with disabilities for barrier-free travel and to address the issue that people with disabilities have nowhere to go, this paper designs a travel recommendation system for people with disabilities based on the recommendation algorithm of users' preferences. Improve the harmony and equal treatment of Chinese society.

1. Introduction

The search engine that relies on manual input of search phrases can no longer satisfy people's various requirements due to the growing amount of information. At the same time, the recommendation system, which can screen out the content of interest for users without the user input precise conditions, has received more and more attention and become an important means to solve the problem of information overload. At the moment, apps like Toutiao and Douyin in addition to online shopping platforms like Taobao and Jingdong make extensive use of the recommendation system. By analyzing user check-in data of LBSN, users' interest tendency can be obtained, and a series of social network recommendation services can be derived. Typical applications include friend recommendation, interest point recommendation and activity recommendation. This paper mainly researches algorithm of user interest preference recommendation[1].The three various types of point of interest recommendation algorithms right now in use consist of the collaborative filtering recommendation algorithm[2], the matrix characterisation approach[3], and the random walk method[4].Among them, collaborative filtering algorithm is the most widely used. Collaborative filtering recommendation algorithms mainly include User-CF algorithm[5] and item-based Item-CF algorithm[6]. In point of interest recommendation, these methods mainly predict and recommend based on users' existing check-in behavior data, but these algorithms are not fully used when introducing social network relationship data. The researchers found that mining implicit information about the project, such as interest preferences, could greatly improve the accuracy of recommendations. Literature[7] converted the user project scoring matrix into the user project attribute scoring matrix, and proposed a collaborative filtering algorithm based on user preferences for project attributes. Literature[8] calculates the similarity between user preferences and project features through labels to realize personalized project recommendation. In literature[9], label information preset by experts is introduced into the similarity calculation process to make up for the sparse problem of scoring matrix. Although the above methods can partially reflect users' interests and preferences and effectively use labels to solve the problem of data sparsity, they fail to take into account that users' interests change over time and ignore the weight of labels in projects[10].

Barrier-free facilities are still being built in China as of this moment. Accessibility facilities are frequently fake. They fail to fully take into account the perspectives of those with impairments. There are some facilities, but they are ineffective and might even be tragic. Travel for those with disabilities is too difficult. There isn't much research on travel tips for disabled individuals in today's culture. Although many people have researched mobility assistance for the disabled, there are essentially no regional recommendations for disability mobility[11]. According to the research, many disabled people are willing to go out to see, but they do not know whether many places are suitable for disabled people because of the imperfect barrier-free facilities in many places, so they have to stay at home. To solve the above problems, we make recommendations according to users' interests, use the recommendation system based on users' interests and preferences, and provide additional options or results according to users' interests and preferences, evaluation scores, etc.

2. Research Basis

2.1. Construction of Correlation Matrix

Table 1: User-project scoring matrix

	I_1	I_2	I_3	…	I_n
U_1	R_{11}	R_{12}	R_{13}	…	R_{1n}
U_2	R_{21}	R_{22}	R_{23}	…	R_{2n}
…	…	…	…	…	…
U_m	R_{m1}	R_{m2}	R_{m3}	…	R_{mn}

Table 2: Item-Label matrix

	A_1	A_2	A_3	…	A_s
I_1	F_{11}	F_{12}	F_{13}	…	F_{1s}
I_2	F_{21}	F_{22}	F_{23}	…	F_{2s}
…	…	…	…	…	…
I_n	F_{n1}	F_{n2}	F_{n3}	…	F_{ns}

The user project scoring matrix R is shown in Table 1. Total project where n said, m said user, said user m for project n score. Preprocessing is done on Table 1. If user m has a score on item n, set the score as 1; If there is no score, the score will be set to 0, forming the user project selection matrix R'. The item label matrix F is shown in Table 2. One s label, total n project, the total said project n contains tags s, n if the project contains tags, s is value is 1, otherwise F_{ns} a value of 0. The user label preference matrix P is shown in Table 3. Total which m said user, s label, said user m to tag s appetite.

Table 3: User-label preference matrix

	A_1	A_2	A_3	…	A_s
U_1	P_{11}	P_{12}	P_{13}	…	P_{1s}
U_2	P_{21}	P_{22}	P_{23}	…	P_{2s}
…	…	…	…	…	…
U_m	P_{m1}	P_{m2}	P_{m3}	…	P_{ms}

2.2. Differences in User Ratings

The concept of score difference between users is introduced in literature [12], which also explains some flaws in conventional similarity measurement techniques. For any two users, the smaller the score difference of the same item, the more similar the two users' preferences, or the higher the similarity between the two users. On the other hand, if there is a greater score disparity between two consumers, their tastes are less comparable and their similarity is lower. Calculating user rating discrepancies frequently involves using the Euclidean distance. The more the value, and the smaller it is, the smaller the difference between people.

3. Methods

3.1. Similarity Calculation based on User Interest Preference

Familiarity and similarity of interests between two people are the main considerations when accepting an unfamiliar location recommended by others. In this paper, familiarity between users is evaluated by analyzing the data of friends relationship between users, and interest similarity between users is evaluated according to the check-in data of users. The trust degree is obtained by combining familiarity and interest similarity. Finally, the recommendation model is shown in Figure 1. Top-N Recommendation Gets the recommendation list.

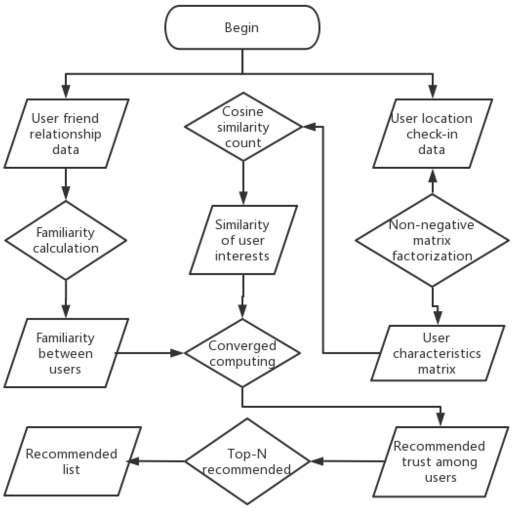

Figure 1: Interest point recommendation model based on user interest similarity and familiarity

3.1.1. User Familiarity Calculation

When recommending points of interest for users, the familiarity between users is an important reference factor, and the higher the familiarity between two people, the more likely the recommended place will be adopted. "A friend of a friend might be a friend of mine" is a widely accepted assumption in social-relations-based recommendation algorithms. Familiarity between users in this article is also determined based on the number of mutual friends. However, familiarity cannot be obtained simply by counting the number of common friends between two users, because familiarity itself is asymmetric. For example, the wider a user's network, or the more active he or she is on a certain platform, the more likely he or she is to have many friends in common with other users. But a person's energy is limited, only from the perspective of familiarity, the familiarity attribute between them is not high. To sum up, the formula for calculating familiarity used in this paper is as follows:

$$\mathrm{Fam}(u,v) = |F_u \cap F_v|/|F_u| \tag{1}$$

In Equation (1),$\mathrm{Fam}(u,v)$Represents the familiarity of user u and user v,$|F_u \cap F_v|$,Is the number of common friends between u and v,$|F_u|$represents the number of friends of user u. The formula shows that the familiarity between user u and user v is proportional to the number of friends between them and inversely proportional to the number of friends between user u. That is, the more active users are, the less familiar they are with other users if they have the same number of common friends. The above situation is the calculation method of familiarity when there are common friends between two users. However, when there are no common friends between two users, according to the three-degree influence rule proposed in literature [5], that is, when two users have no common friends but the distance between two users is three, there is still a certain degree of familiarity. In this paper, when there is no mutual friend (distance is 3) between two users, the calculation formula of familiarity is as follows:

$$\mathrm{Fam}(u,v) = \frac{1}{2} \cdot \sum_a R(u,a)\, R(a,v) \tag{2}$$

In Formula (2), Fam(u,v) represents the familiarity between user u and user v, and a is any other user other than user u and user v.

3.1.2. Calculation of User Interest Similarity

The key problem of classical collaborative filtering algorithm is the calculation of similarity, among which user similarity is exactly user interest similarity. When measuring the interest similarity, the scoring matrix of the project is used. The commonly used methods include cosine similarity, correlation similarity and so on. In this paper, cosine similarity is adopted, and its calculation formula is

$$\mathrm{sim}(u,v) = \cos(\vec{u},\vec{v}) = \frac{\sum_{i=1}^{n} R_{ui} R_{vi}}{\sqrt{\sum_{i=1}^{n} R_{ui}^2}\sqrt{\sum_{i=1}^{n} R_{vi}^2}} \tag{3}$$

In Formula (3), sim(u,v) represents the similarity between user u and user v; u and v respectively represent the scoring vector of user u and user v; n is the number of items in the scoring matrix; R_{ui} and respectively represent the score of user u and user v on item i[5].

However, because of the sparsity of the user score matrix, it is not effective to calculate the interest similarity between users by using cosine similarity directly. In this paper, the user place check-in matrix is decomposed into the product of two non-negative matrices and $H_{k\times n}$by non-negative matrix decomposition (NMF), where k is the characteristic number, is the user characteristic matrix, and is the location characteristic matrix, making $R_{m\times n} = W_{m\times k} \cdot H_{k\times n}$.In the process of solving NMF, it is assumed that the noise matrix is$E \in R_{m\times n}$ and obeys Gaussian distribution. The E = R - WH, solving process is to find the right W and H$||E||$ is minimal. Since noise obeys Gaussian distribution, the maximum likelihood function is

$$L(W,H) = \prod_{i,j} \frac{1}{\sqrt{2\pi}\sigma_{ij}} \exp(-\frac{(R_{ij}-(WH)_{ij}{}^{2}}{2\sigma_{ij}}) \tag{4}$$

After taking the logarithm, the log-likelihood function obtained is

$$\ln L(W,H) = \sum_{i,j} \ln \frac{1}{\sqrt{2\pi}\sigma_{ij}} - \frac{1}{2\sigma_{ij}} \cdot \sum_{i,j} \left[R_{ij} - (WH)_{ij}\right]^2 \tag{5}$$

It is assumed that the variance of the noise of each data point is the same, so that the logarithmic likelihood function is the maximum value, and the following objective function is the minimum value.

$$J(W,H) = \frac{1}{2} \sum_{i,j} \left[R_{ij} - (WH)_{ij}\right]^2 \tag{6}$$

The loss function of 2 norm loss function, and because$(WH)_{ij} = \sum_k W_{ik} H_{kj}$, strives for the partial derivatives$\frac{\partial J(WH)}{\partial W_{ik}} = H_{ik}$,

$$so\frac{\partial J(W,H)}{\partial W_{ik}} = (RH^T)_{ik} - (WHH^T)_{ik} \tag{7}$$

The same way

$$\frac{\partial J(W,H)}{\partial H_{kj}} = (W^T R)_{kj} - (W^T W H)_{kj} \tag{8}$$

Gradient descent method is used for iteration, and the iteration formula is as follows:

$$W_{ik} = W_{ik} - \alpha_1 [(RH^T)_{ik} - (WHH^T)_{ik}] \tag{9}$$

$$H_{kj} = H_{kj} - \alpha_2 \left[(W^T R)_{kj} - (W^T W H)_{kj}\right] \tag{10}$$

$$take\alpha_1 = \frac{W_{ik}}{(W^T W H)_{ik}} \qquad \alpha_2 = \frac{H_{kj}}{(WHH^T)_{kj}}$$

The final iteration is

$$W'_{ik} = W_{ik} \cdot \frac{(RH^T)_{ik}}{(WHH^T)_{ik}} \tag{11}$$

Will eventually iterative into, iterative calculation to the objective function.

$J(W,H) = \frac{1}{2} \sum_{i,j} \left[R_{ij} - (WH)_{ij}\right]^2$value is less than 0.001, the non-negative matrix W_{mk}namely characteristic matrix for the user. The interest similarity between users is calculated according to the user characteristic matrix, and the cosine similarity calculation formula is adopted, as shown below:

$$sim(u,v) = \cos\langle \vec{u} \cdot \vec{v} \rangle = \frac{\sum_{i=1}^{k} W_{ui} W_{vi}}{\sqrt{\sum_{i=1}^{k} W_{ui}^2} \sqrt{\sum_{i=1}^{k} W_{vi}^2}} \tag{12}$$

Among them, the sim (u, v) said users u and v interest similarity,$\vec{u}$and$\vec{v}$respectively users u and v characteristic vector and the k number, characterized by W_{ui}andW_{vi} said users u and v on the characteristics of the I score.

3.1.3. User Recommendation Trust Calculation

By unifying user familiarity and user interest similarity, user recommendation trust can be obtained, and its calculation formula is

$$\mathrm{T(u,v)} = \alpha \cdot \mathrm{Fam(u,v)} + (1 + \alpha) \cdot \mathrm{Sim(u,v)} \quad (13)$$

In Equation (13), $0 \le \alpha \le 1$.

3.1.4. Personalized Interest Point Recommendation

According to the idea of collaborative filtering, based on the unified user recommendation trust, search the user set Ts near the target user u (take the first S, S is the length of the adjacent users), take the user check-in location set in the set Ts, and remove the location already checked in by the target user u as the location set L to be recommended. Then, according to the check-in information of neighboring users, the target users' preference degree to the check-in place can be predicted, and the calculation formula is as follows

$$\mathrm{Int(u,i)} = \frac{\sum_{v=1}^{S} T_{uv} \cdot C_{vi}}{\sum_{v=1}^{S} T_{uv}}, i \in L \quad (14)$$

In Formula (14), Int(u,i) is the preference degree of target user u to location i, S is the length of neighboring users, is the recommendation trust degree of user v to target user u, and C_{vi} is the check-in times of user v at location i. Sort according to the value of Int(u,i), and output Top-N locations as recommended locations [13].

3.2. Similarity Calculation Considering Score Differences

For things with the same rating value, various users may show distinct interests preferences. Currently, the standard formula for computing cosine similarity is typically utilized to resolve this issue, and the similarity is corrected using the average user score. The impact of user and project quality differences on the calculation of similarity is also disregarded by this method.

The first is the influence difference between users. The old similarity calculation method simply takes into consideration the common score items between users by default; it does not account for the influence brought on by non-common score items. For instance, user A and user B's scoring vectors for four distinct items are (4,4,0,0) and (4,4,2,3), respectively. According to the modified cosine similarity calculation formula, the findings indicate that user A and user B have the exact same interest when just the common scoring items of the two users are taken into account.

Secondly, the difference in the quality of the project itself is also the reason for the deviation of similarity calculation. For example, a large number of users give similar scores to a certain project, and in this case, the calculated similarity between users is often high, but it does not completely mean that users have identical interests and preferences. This shows that the difference in the quality of the project itself will also lead to the deviation of the calculated similarity results.

Table 4: Definition of mathematical symbols in this section

symbol	interpretation
$C_{u \cdot v}$	User impact factor between user u and user v
C_i	Impact factor for project i
C_{max}	The maximum value inC_i
C_{min}	The minimum value inC_i
$C_i^{'}$	The project impact factor after normalization treatment

This research introduced the user impact factor and project impact factor, respectively, to address the aforementioned issues and increase the precision of the user similarity computation. Table 4 lists the interpretation of mathematical symbols in this section. User influence factor can correct the influence of different users' scored items in similarity calculation. Item influence factor can correct the influence of item quality in similarity calculation.

3.2.1. Influence Factor

In order to reflect the different degree of interaction between different users, the user impact factor$C_{u,v}$ is introduced into the calculation of similarity between users.Its definition is shown in Equation (15)

$$C_{u,v} = 1 - e^{-\frac{I_{u,v}}{I_u}} \tag{15}$$

As can be seen from Equation (15), when calculating the user impact factor, it is necessary to first find the set of items that both user u and user v have overrated.

In order to reflect the impact caused by the quality difference of the project itself, the project impact factorC_i should be introduced into the calculation of correcting the deviation of user scores to solve the adverse impact caused by the quality of the project itself in the calculation of user similarity. Its definition is shown in Equation (16)

$$C_i = \sqrt{\frac{1}{|U_i|}\sum_{u=1}^{|U_i|}(R_{u,i} - \bar{R}_i)^2} \tag{16}$$

The greater the difference between users' score values for item i, the better the project can distinguish between different users' interests and preferences, and the greater the C_ii value. According to equation (16), project impact factors of all projects can be calculated and normalized. The normalization processing formula is shown in Equation (17).

$$C_i' = \frac{C_i - C_{min}}{C_{max} - C_{min}} \tag{17}$$

3.2.2. Improved Similarity Calculation Formula based on Score Difference

The impact of the project's quality and the degree of mutual influence between users on the similarity calculation is comprehensively taken into account in this part, and a more effective similarity calculation approach is then suggested[14]. Based on the modified cosine similarity formula, user impact factor $C_{u,v}$ and project impact factor are introduced into the algorithm, as shown in equation (18)

$$sim_R(u,v) = \frac{\sum_{i \in I_{u,v}} C_{u,v} \times C_i' \times (R_{u,i} - \overline{R_u}) \times (R_{v,i} - \overline{R_v})}{\sqrt{\sum_{i \in I_u}\{C_i' \times (R_{u,i} - \overline{R_u})\}^2}\sqrt{\sum_{i \in I_v}\{C_i' \times ((R_{v,i} - \overline{R_v}))\}^2}} \tag{18}$$

4. Application

User modeling, recommendation object modeling, and recommendation algorithm modeling are the three key components in this research. Figure 2 depicts the general recommendation system model flow. The recommendation system is used to match the feature information in the recommendation object model with the interest demand information in the user model. In order to locate the recommendation object that the user would be interested in and to offer it to them, the relevant recommendation algorithm is utilized simultaneously for computation and screening.

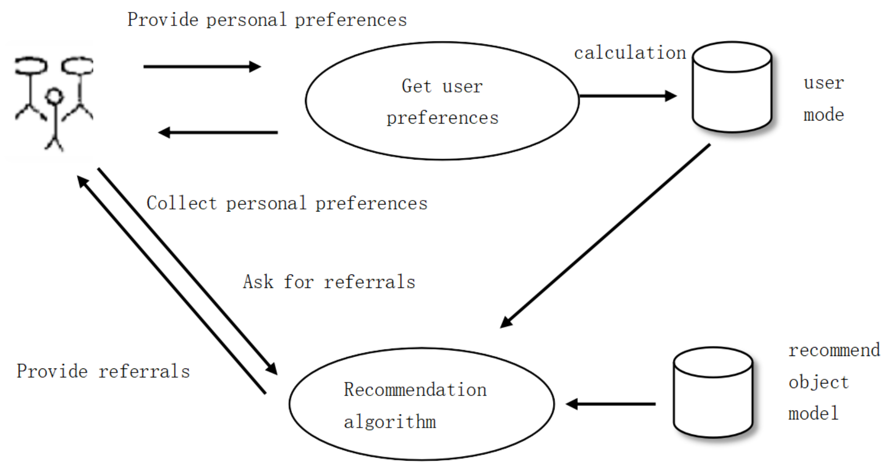

Figure 2: Recommendation system model flow

When using this system at the very beginning, it is bound to face the problem of cold start. The initial user data will not be too large, and the participation of users may not be large, so we can set up some effective interest preference information options. When users start to use this recommendation system, users are allowed to choose their interest options. We recommend users according to the above algorithm and their interest preferences. In addition, when there is no user data, it first makes a basic survey on the construction degree of barrier-free facilities in streets and scenic spots all over the country. There is a basic evaluation data of a place, and the preference information is corresponding to the location data. The system will provide travel location recommendation at the beginning, and then save the user's historical records and scores. According to the score difference calculation and other implementation, more appropriate places are recommended for old users, and more optimized initial recommendations are made for new users.

The initial step in this recommendation technique is to extract the recommended objects' content features and match them with the user model's users' interests and preferences. Users may receive recommendations for recommended objects that have a high degree of matching. Users can rate a location in this system after a trip based on factors like the scenery, the overall experience, the availability of amenities for people with disabilities, etc.

When the database is sufficient and enough data can be analyzed and utilized, the similarity can be calculated between users, between users and places, and between places. Through the calculation and combination of many aspects of the similar degree, the most suitable recommendation for users, so that users more love and trust the system. Can achieve the user clearly eager to travel, but because of the unsatisfactory external environment and stay at home, through the use of this system, under the recommendation of this system has a suitable and comfortable travel experience, gradually more and more willing to travel. It can also drive more users with related needs to go out to see. The travel of the disabled is no longer a problem, and they can even decide the travel location and complete the travel alone.

5. Conclusion

In order to address the issues of sparse data in the conventional recommendation algorithm based on collaborative filtering, the difference in user scores affecting the calculation results of similarity, and the low timescales caused by the change in user interest over time, this paper studies the current issues of travel for people with disabilities and proposes an improved hybrid recommendation algorithm based on user interest preference.

The method first determines the user's preference for the project attribute based on the TF-IDF concept and fills the sparse matrix based on an examination of the user's history score data. The difference between the user's impact factor and the modified score for the project quality factor based on the modified cosine similarity calculation method is then introduced in the user's similarity calculation. Then, various time decay functions are given to represent the change in user interest while taking into account the impact of time on the computation of user interest preference and prediction score. Through the algorithmic representation, the travel advice for the disabled may be made a reality, and issues like having nowhere to go and insufficient barrier-free facilities in different locations can be resolved, making our society more humane.

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