



Personalized Recommendation Method of Online Career Guidance Curriculum Resources Based on Collaborative Filtering

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Abstract. Aiming at the problems of low recommendation efficiency and inaccurate recommendation results of existing resource recommendation algorithms, this paper proposes a personalized recommendation method design of online career guidance curriculum resources based on collaborative filtering. Firstly, analyze the principle of personalized recommendation of course resources, then establish a user social network model, and calculate the similarity based on user interest preferences and course resource ratings. Finally, based on this, complete the design of personalized recommendation methods for online employment guidance course resources. The feasibility of the proposed method was demonstrated through comparative experiments. The test results showed that the MAE value of the proposed method was between 0.7 and 0.78, the average recommendation time was less than 13.3 ms, and the F-value was higher than 0.95, which is superior to the comparative method. The recommendation efficiency is higher and the recommendation results are more accurate, indicating good application value.

Keywords: Collaborative Filtering · Employment Guidance Courses · Curriculum Resources · Personalized Recommendations

1 Introduction

Nowadays, the job market is becoming increasingly competitive, and many graduates or job seekers feel confused when facing the employment problem. They don't know how to choose the industry, the company and how to improve their abilities. In order to better guide job seekers, many universities and job centers provide a variety of career guidance course resources, which cover the content of resume making, career planning, interview skills, workplace psychology and other aspects, so it has good reference value for job seekers [1]. However, for different job seekers, due to the differences in learning background, personal hobbies, job hunting direction and other factors, each person needs different course recommendation, but manual screening and recommendation requires a lot of time and energy [2]. In the face of such huge course resources, how to provide the most suitable course recommendation for job seekers becomes more complicated.

As proposed in reference [3], a personalized recommendation system for course resources based on data mining is proposed. It utilizes 22 servers to form a server module, and uses an S3C3210x processor for processing to form a hardware system design. The software mainly uses the Orange toolbox to mine course resource data, and then uses hybrid recommendation technology to achieve personalized recommendation. A personalized recommendation algorithm for large-scale open online course resources is proposed in reference [4]. It first clusters online course resources, then generates candidate queues for course resource recommendation. Through column and set operations, the queue length with behavior height that overlaps with the user's own information is obtained. Finally, course resource recommendation is implemented based on the TF-IDF method. A multi task feature recommendation algorithm integrating Knowledge graph is proposed in literature [5], which is based on multi task feature learning and embeds Knowledge graph in tasks; By establishing higher-order connections between potential features and entities through cross compression units between tasks, a recommendation model is established, achieving precise recommendation of course resources based on learners' goals, interests, and knowledge levels. After verification, all three methods have problems with low recommendation efficiency and low recommendation quality. Therefore, further research should be conducted on them.

Collaborative filtering is an algorithm widely used in the field of personalized recommendation. Its principle is to find users with similar preferences and views through the analysis of historical user behavior data, and then recommend similar content to target users according to their evaluation or selection records. The online resource recommendation system based on collaborative filtering algorithm has been widely used in education, e-commerce and other fields, and has achieved good recommendation results, with high user satisfaction.

Based on this, this study will improve the collaborative filtering algorithm, establish the social network model, and realize the calculation of user similarity from two aspects, so as to enhance the individuation and accuracy of the recommendation algorithm, better grasp the user needs, and improve the efficiency of resource utilization. At the same time, this study will also explore data processing and model optimization problems, improve the running speed and stability of the algorithm, and further promote the utilization rate and quality of online career guidance course resources. In conclusion, this study aims to provide personalized and intelligent employment guidance services for job seekers and make positive contributions to talent training and career development.

2 Principles of Personalized Recommendation of Course Resources

Collaborative filtering is based on a collective wisdom. Users with similar interests may have preferences for similar projects. The collaborative filtering algorithm first needs to find a set of neighbor users with similar interests to the target object in the system, and then predict and judge whether to recommend according to the preference of the neighbor users in the set for the predicted items. The most important steps are: collecting user preferences, finding neighboring users or similar items, and calculating recommendations. The user preference information in the process of collecting user preferences comes from user data, mainly including basic user information, user learning data, user

behavior data, et al. The earliest collection of user preference information is mainly based on user display data, such as rating, voting, forwarding, favorites, comments, etc., which is called display rating. Later, with the development of technology and the need for recommendation accuracy, recommendation based on data mining technology is widely studied and used. Users' implicit data are obtained through click rate, purchase behavior, page stay time, etc., and weighted into users' score on resources, which is called implicit score. The former is more intuitive and can accurately reflect users' preferences for resources, while the latter indirectly obtains resource scores through relevant data to make up for the sparse data caused by the lack of real scores. However, its disadvantage is that these data cannot reflect users' real preferences in some cases, resulting in low accuracy of scores. Finding similar neighbors and items is the core step of collaborative filtering recommendation. Common similarity algorithms include cosine similarity, Euclidean distance and Pearson correlation coefficient.

The collaborative filtering recommendation algorithm does not consider the content information of items in the recommendation process, so it overcomes the problem of extracting the content features of video, audio and other types of items in the content-based recommendation algorithm, so that the system needs less information when making recommendations and is easier to obtain. At the same time, the recommendation system is not limited to text items, so it is more universal.

However, collaborative filtering algorithm also has some shortcomings, that is, in the actual recommendation system, the number of items purchased or evaluated by users is often very small in a massive number of projects. In this case, the quality of the set of near neighbor users sought for target users based on similarity will be greatly reduced. And this inaccurate set of neighbor users will affect the accuracy of the results produced when the system makes predictions for the target users later. When a user has just registered as a new user, there is no history of the new user in the system, so it is not possible to find the user's nearest neighbor set based on its evaluation of the project through similarity calculation.

On this basis, the algorithm is improved and the personalized recommendation method of online career guidance course resources is researched.

3 Establish a User Social Network Model

Traditional collaborative filtering algorithms only rely on users' historical scores for recommendation. Firstly, the global calculation of similarity among users leads to a large number of redundant calculations, which increases the computing burden and response time of the system. Secondly, when there are illegal users in the system deliberately imitate the browsing records of some real users of the system, resulting in the illusion that illegal users and real users are very similar, and then deliberately score high on certain resources to make certain resources appear in the recommendation results of real users of the system, this kind of support attack will reduce the robustness of the system [6]. To solve the above problems, this paper proposes to establish a user social network model to screen out the target user trust user set. By utilizing users' social information to establish a social network model, a trust set is established based on the model. Transforming the previous global similarity calculation into local similarity calculation in the trust

set can effectively reduce system complexity and improve real-time performance. At the same time, the trust set can filter out unrelated malicious users, ensuring that user recommendations are not maliciously misled and increasing the robustness of the system. Social network models can effectively increase the accuracy of the nearest neighbor set, thereby alleviating the impact of data sparsity.

There are two main variables in the user social network model. One is trust capacity, which represents the degree of trust that the target object can propagate to its friends and friends of friends; The second is trust traffic, where the target object allocates the level of trust based on the strength of their social relationships with other users [7].

The establishment of user social network model is mainly divided into three steps:

Step 1: First, set the target user as the start node. Assume that the target user fully trusts the initial trust capacity set by himself is 1.

Step 2: A person will ask the people around him one by one when consulting his friends. Based on this idea, breadth-first search method is adopted to allocate the trust capacity for the social circle of the target user (starting node). The formula for calculating the trust capacity of subsequent nodes is as follows:

$$Cap_{suc} = Cap_{pre} \times w_{ij} \quad (1)$$

Among them, Cap_{suc} represents the trust capacity of the current node, Cap_{pre} represents the trust capacity of the previous node, and w_{ij} represents the social intensity coefficients of users i and j [8]. The calculation formula is as follows:

$$w_{ij} = \begin{cases} SoSim_{ij}, inter_{ij} = 0 \\ \frac{2 \times inter_{ij} + SoSim_{ij}}{inter_{max}^i + SoSim_{ij}}, inter_{ij} \neq 0 \end{cases} \quad (2)$$

where, $inter_{ij}$ is the number of interactions between user i and j , and $inter_{max}^i$ is the maximum number of interactions between user i and other users. $SoSim_{ij}$ represents the social circle similarity of users i and j . When the interaction times of user i and j are 0, $SoSim_{ij}$ is used to represent w_{ij} , and the calculation formula is as follows:

$$SoSim_{ij} = \begin{cases} 1, \frac{JaSim_{ij}}{2 \times avg(JaSim)} \geq 1 \\ \frac{JaSim_{ij}}{2 \times avg(JaSim)} \end{cases} \quad (3)$$

Among them, $JaSim_{ij}$ is the degree of overlap of friend circles, $avg(JaSim)$ is the average degree of overlap of friend circles for all users in the system [9]. $SoSim_{ij}$ represents the degree of overlap between users i and j 's circle of friends. If the subsequent nodes are not the direct circle of friends of the target object, but rather the non direct relationship of friends, then according to the idea of the Ford Fulkerson algorithm, a maximum path can be found to transfer the trust relationship and obtain the trust capacity of the subsequent nodes.

Step 3: Collect the trust capacity of all users in the network model and establish the trust user set of target users.

Let CD store the trust capacity propagated by all nodes in the social network model of user u through the initial node, where the node whose value is greater than threshold

T can enter the candidate set, and CDF is the candidate set of users. TL is the set of trusted users of user u . The calculation process is as follows:

- (1) Set node u as the starting node;
- (2) From u 's local social network adjacency matrix D , find out the user who can join the candidate user set. The user's trust capacity needs to be greater than the threshold T set by the system, and has not been selected into the candidate user set CDF and the trusted user set TL [10].
- (3) Find the largest user v in CDF by comparing the trust capacity, and then place it in TL ;
- (4) Subtract 0.1 from user v 's value in CD , and then set $[u, v]$ to 1 in D ;
- (5) Take user v as the starting node and repeat step (2), and then delete user v from CDF [11];
- (6) If CDF is empty, the trusted user set of user u is output. Otherwise, repeat step (3) to obtain the trust set of target user u after the algorithm ends. In the following text, use an improved similarity calculation method to calculate the similarity between users and u in the trust set, and then obtain the nearest neighbor set [12].

3. User similarity calculation.

This article adopts a combination of interest preference model and resource scoring method for neighbor calculation. Firstly, it collects neighbor users based on the user interest preference model, and secondly, it collects neighbor users based on user learning records:

1) Similarity calculation based on user interest preferences

a. User knowledge level similarity

The similarity of knowledge level of user u and user v is defined as $S(u, v)$, and $S(u, v)$ is 1 when the range of knowledge level of the two users is consistent. $S(u, v)$ is 0 when two users' knowledge ranges are inconsistent [13]. Where, S_u represents the knowledge ability level of user u , and S_v represents the ability level of user v , then the knowledge level similarity $S(u, v)$ of user u and user v can be calculated as follows:

$$S(u, v) = \begin{cases} 1, S_u = S_v \\ 0, S_u \neq S_v \end{cases} \quad (4)$$

b. Interest tag similarity

The similarity of interest labels between user u and user v is defined as $I(u, v)$, with user u 's interest label set $I_u = \{I_{u1}, I_{u1}, \dots, I_{um}\}$ and user v 's interest label set $I_v = \{I_{v1}, I_{v1}, \dots, I_{vm}\}$, where the same number of labels has a value of k , then the similarity of interest labels $I(u, v)$ between user u and user v is calculated using the following formula:

$$I(u, v) = \frac{k}{m + n + k} \quad (5)$$

c. Curriculum preference similarity

The similarity of career guidance course preferences of user u and user v is defined as $J(u, v)$, user u prefers course set $J_u = \{I_{u1}, I_{u1}, \dots, I_{um}\}$, user v prefers

course set $J_v = \{I_{v1}, I_{v1}, \dots, I_{vm}\}$, where the number of the same course is h , then the calculation formula of course preference similarity $I(u, v)$ of user u and user v is as follows:

$$I(u, v) = \frac{h}{m + n + h} \quad (6)$$

d. Employment Guidance Learning Scope Preference Similarity

The similarity of the employment guidance learning range between user u and user v is represented by $L(u, v)$, where user u has a learning range set of $L_u = \{L_{u1}, L_{u1}, \dots, L_{um}\}$ and user v has a learning range preference set of $L_v = \{L_{v1}, L_{v1}, \dots, L_{vn}\}$, where the same number of range values are r [14, 15]. The formula for calculating the course preference similarity $L(u, v)$ between User a and User b is as follows:

$$L(u, v) = \frac{r}{m + n + r} \quad (7)$$

Similarly, the similarity of user preference for career guidance teachers is calculated by the same principle. The similarity value of user teacher preference is defined as $D(u, v)$, then the user similarity $SoSim_{ij}$ based on the user interest preference model is shown as follows:

$$SoSim_{ijmodel} = \alpha S(i, j) + \beta I(i, j) + \chi J(i, j) + \delta L(i, j) + \varepsilon D(i, j) \quad (8)$$

Among them, $\alpha, \beta, \chi, \delta, \varepsilon$ is the weight factor, and its sum is 1.

2) similarity calculation based on the user resources score:

Step 1: Assume that the user rating data contains m user set and n career guidance course resources, and generate a “user-1 rating” matrix according to the user’s learning record. $V(m, n)$ represents the rating of resources as shown in Table 1.

Table 1. User-course resource scoring matrix

	Career guidance Course Resources 1	Career guidance Course Resources 2	Career guidance Course Resources 3	...	Career guidance Course Resources n
User 1	$V_{1,1}$	$V_{2,1}$	$V_{3,1}$...	$V_{m,1}$
User 2	$V_{2,1}$	$V_{2,2}$	$V_{2,3}$...	$V_{2,n}$
...

Step 2: Construct a data structure of “Employment Guidance Course Resource One User” and obtain a set of user neighbors who have studied the same course, as shown in Table 2.

Table 2. Employment guidance curriculum resources a user matrix

	User 1	User 2	User 3	...	User n
Course Resources 1	$U_{1,1}$	$U_{1,2}$	$U_{1,3}$...	$U_{1,n}$
Course Resources 2	$U_{2,1}$	$U_{2,2}$	$U_{2,3}$...	$U_{2,n}$
...
Course Resources m	$U_{m,1}$	$U_{m,2}$	$U_{m,3}$...	$U_{m,n}$

Step 3: Based on the co rated course, a modified cosine similarity algorithm is used to calculate the similarity values between users. The average scores of users i and j in the co rated items are R_i, R_j , respectively. The calculation formula is as follows:

$$SoSim_{ij\text{score}} = \frac{\sum_{k \in I_{ij}} (R_{i,k} - \bar{R}_i)(R_{j,k} - \bar{R}_j)}{\sqrt{\sum_{k \in I_i} (R_{i,k} - \bar{R}_i)^2} \sqrt{\sum_{k \in I_j} (R_{j,k} - \bar{R}_j)^2}} \quad (9)$$

Because the cosine similarity algorithm does not consider the problem of user rating differences, but only distinguishes in the direction, it is possible to calculate a high similarity even if there are obvious differences between two resources. The modified cosine algorithm compensates for this shortcoming by subtracting the average user rating of the resource. Finally, the result values of the two calculation methods are summed. The rule of calculation is to superimpose the two similarity values of the same user. If the user has no result value in one of the calculation methods, the similarity value of the user in this dimension is 0 by default. The final similarity of the user is defined as $SoSim_{ij\text{final}}$, λ is the weight factor, then the calculation formula of the result is as follows:

$$SoSim_{ij\text{final}} = \lambda SoSim_{ij\text{model}} + (1 - \lambda) SoSim_{ij\text{score}} \quad (10)$$

After calculating the results, $SoSim_{ij\text{final}}$ is sorted by size, and the top N items are selected as sub items of the nearest neighbor user set in descending order. Finally, recommendations are made based on the resource prediction score of the nearest neighbor. The search and calculation of recent neighbors is the focus and key of this article's research. The selection of neighbor users has a significant impact on the final recommendation project, as these resources are all sourced from their neighbors. Accurate neighbor relationships determine the accuracy of recommendation results. Based on the calculation of similar neighbors based on user interest preference model, this paper summarizes students' interest preference from attributes, behaviors, students' learning ability, project attributes and other aspects, and captures students' interest preference from multiple perspectives. For new users, no scoring resource can be used for recommendation calculation through interest preference model to solve the cold start problem. For the problem of data sparsity, the calculation based on the user's interest preference model is a supplement to the calculation of resource score. The combined method of the two will improve the quality and reliability of the user's neighbors and provide accurate data resources for the final recommendation.

4 Personalized Recommendation of Online Employment Guidance Course Resources

Through the above extended neighbors based on users' interests and preferences and direct neighbors based on course resource scoring, predict the unused and unrated items of the target users in the final neighbor user resource project, and select the first item N with the highest predicted score as the recommended item to the users. The calculation method is as follows:

$$P_{u,j} = \bar{R}_u + \frac{\sum_{v \in s(u)} (R_{v,j} - \bar{R}_v) \cdot SoSim(u, v)}{\sum_{v \in s(u)} |SoSim(u, v)|} \quad (11)$$

During the period, $P_{u,j}$ represents the predicted score of user u on unrated resources, $s(u)$ represents a set of similar neighboring users for user u , \bar{R}_u represents the average score of user u 's rated resources, and \bar{R}_v represents the average score of neighboring user v 's rated resources.

To sum up, complete the design of personalized recommendation method for online career guidance curriculum resources based on collaborative filtering.

5 Experimental Analysis

5.1 Experimental Environment Settings

This research experiment is carried out based on two laptops, and the experimental environment is set up as shown in Table 3.

Table 3. Experimental Environment Settings

Index	Parameter
Computer	Two sets
Memory	4 GB
Processor	Inter(R) CORE (TM)-i5-7200U@2.60 GHz
Operating system	Windows 10
The server	Apache/2.4.26(Win32)
Database	MySQL

In order to test the performance of Collaborative filtering recommendation based on user interest preferences proposed in this study, 40 testers were selected to test the system. These 40 students are students from educational technology majors, and the test process is as follows (Fig. 1)

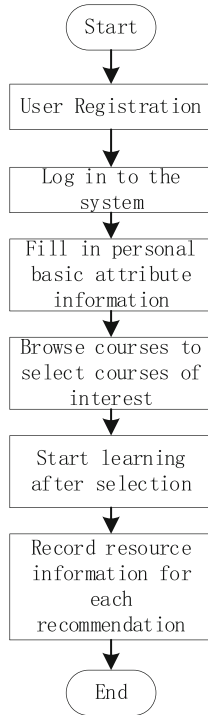


Fig. 1. Test Flow Chart

In this test, a total of 40 students studied and rated 200 career guidance course resources, with a total of 250 scoring records. The main purpose of this test is to test the recommendation effectiveness of the system's recommendation methods. Due to limitations in the experimental environment and conditions, the quality of the testers did not achieve the expected results, and the number of testers was relatively limited. However, the overall recommendation effect was relatively obvious, achieving the expected value.

5.2 Selection of Experimental Indicators

In this test, mean absolute error (MAE) was selected as one of the evaluation indexes to evaluate the performance of the method. MAE determines whether the recommendation is accurate by comparing the degree of deviation. Deviation degree refers to the error between the predicted score of the recommendation algorithm and the actual score of users. The lower MAE value is, the smaller the error between the predicted score and the actual score is, and the more accurate the recommendation is. Conversely, the higher the MAE value, the greater the error and the worse the recommendation effect. When the number of resources scored by the user is defined as n , the system predicts that the user's

score on resource i is X_i , and the actual score on resource i is y_i , then the calculation formula of MAE index is shown as follows:

$$MAE_i = \frac{\sum_{j=1}^n |x_i - y_i|}{n} \quad (12)$$

Introduce the comprehensive evaluation index F-measure to evaluate the accuracy and recall of the testing system. The range of F-measure is between 0 and 1, and the larger its value, the better the performance of the classifier and the stronger the predictive ability of the model. When F-measure is equal to 1, it indicates that the model's prediction is very accurate and can perfectly match the required results; When F-measure is equal to 0, it indicates that the predicted value of the model is completely useless and cannot be evaluated for its effectiveness. The specific calculation formula is as follows:

$$F = \frac{2PR}{P + R} \quad (13)$$

In the formula, F represents the F-measure value, P represents the accuracy rate of recommendation results of employment guidance course resources, and R represents the recall rate of recommendation results of employment guidance course resources.

5.3 Analysis of Experimental Results

Based on the above, literature [2] system and literature [3] system were selected as comparative methods to conduct personalized recommendation of online employment guidance course resources together with the proposed method. Multiple tests were conducted, and the changes in MAE values of the three methods as the algorithm iterated are compared as shown in Fig. 2.

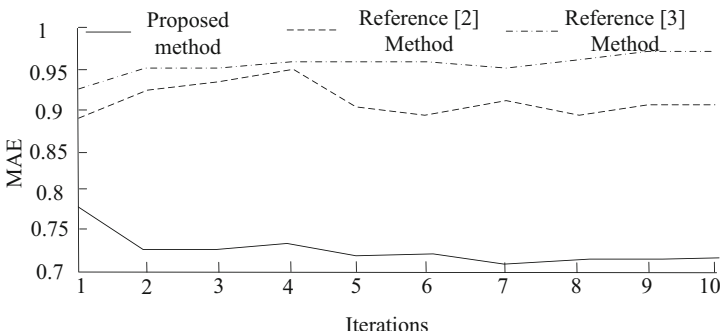


Fig. 2. Changes in MAE values

As shown in Fig. 2, the MAE values of the three methods are also constantly changing with the change of the number of iterations, but the trend is not large. The MAE values obtained by the proposed method are relatively stable, but decrease with the increase

of the number of iterations, and their values are stable between 0.7 and 0.78, while the other two methods are stable, both higher than 0.89. Moreover, its value varies greatly and does not decrease as the number of iterations increases, so the proposed method has higher recommendation accuracy. Next, the recommendation efficiency of the three methods is compared, and the results are shown in Table 4.

Table 4. Average Recommended Time

Iterations	Average recommended time of the proposed method/ms	Reference [2] Method Average Recommended Time/ms	Reference [3] Method Average Recommended Time/ms
1	13.2	44.2	46.2
2	11.1	45.5	43.3
3	12.4	44.8	44.2
4	11.2	44.9	42.5
5	11.9	42.3	42.8
6	12.3	45.6	45.2
7	12.6	43.3	43.2
8	11.4	44.2	44.6
9	13.3	44.6	43.9
10	12.6	44.6	45.6

According to Table 4 above, it can be seen that the recommendation time of the proposed method is the shortest, which is all less than 13.3 ms, while the recommendation time of the method in literature [2] is at least 42.3 ms, and the recommendation time of the method in literature [3] is at least 42.5 ms. Therefore, the recommendation efficiency of the proposed method is higher and it has greater application value.

Next, the F value of the three methods changes with the iteration of the algorithm, as shown in Fig. 3.

As shown in Fig. 3, the F value of the system established by the proposed method is all higher than 0.95, while the method in literature [2] and the method in literature [3] are both lower than 0.85. Therefore, the recommended performance of the proposed method resources is better and it has greater application value.

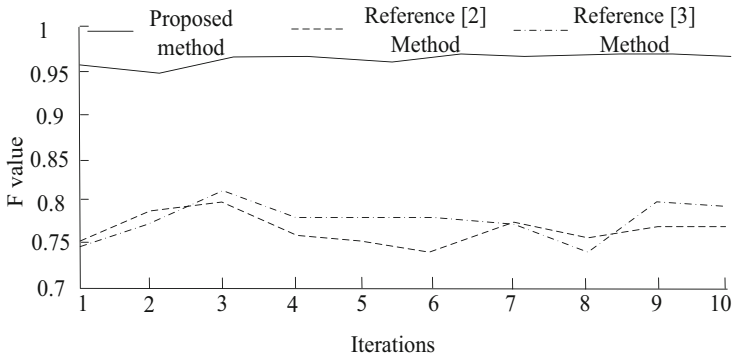


Fig. 3. Changes in F-value

6 Conclusion

The development and popularization of internet technology have greatly enriched the types and channels for people to obtain information, and also brought great convenience to people's work, study, and life. However, these vast amounts of data have already exceeded the limits that individuals can accept and have caused the famous "information overload" problem, which seriously affects the efficiency of users to obtain effective information. As a result, personalized recommendation systems have emerged. This research proposes a personalized recommendation method of online career guidance curriculum resources based on collaborative filtering to solve the problem of poor recommendation effect of contemporary graduates' career guidance curriculum resources. In order to realize the personalized recommendation of career guidance course resources, the author first establishes the user social network model and then calculates the user similarity from two aspects. The results show that the MAE values of the proposed methods are stable, ranging from 0.7 to 0.78, the average recommendation time is less than 13.3ms, and the F values are higher than 0.95, which is better than the comparison methods and has greater application value. Although this study has already achieved certain research results, there are still some shortcomings in the exploration of curriculum resources for employment indicators, which is also the next research direction.

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