Satellite-to-ground communication decision system based on knowledge graph

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Abstract. The knowledge graph relies on the powerful knowledge aggregation ability to bring new space for progress to the satellite-to-ground communication decision-making system, and it performs better in accuracy, debugging, scalability and decoupling. Then, based on the user-based collaborative filtering algorithm, a collaborative filtering algorithm fused with path loss is proposed. Based on the path loss formula for the free propagation of radio waves, the similarity factor is derived, and the similarity calculation formula more in line with satellite-to-ground communication is obtained. Through the simulation results, it can be seen that the improved algorithm has improved accuracy and recall rate, resulting in more satisfactory recommendation results.

1. Introduction
In the complex satellite-to-ground communication environment [1], the communication intelligent decision-making system can make intelligent decision output under given reference criteria and constraints. Some researchers through equivalent communication parameters [2-4] and interference parameters, and use double-layer reinforcement learning [5] algorithms to complete the decision. Some researchers use case-based reasoning algorithm [6], search the same case from the search unit, use artificial bee colony [7] and other algorithms in the decision-making unit to find the optimal solution, and modify the unit to monitor the results. However, the definition of the case in this method limits the diversity of input, and the calculation of case similarity is complicated and the scalability is poor.

This paper proposes to establish a decision-making system through the knowledge graph[8] combined with a collaborative filtering algorithm fused with path loss [9]. The knowledge graph stores communication parameters, environmental parameters, interference parameters and other related information, combines traditional collaborative filtering algorithms with the formula of radio wave transmission distance loss, increases similarity calculation parameters, and makes the results more accurate.

2. Methods and Related Work

2.1. Build a knowledge graph
The knowledge graph contains a total of communication scenarios, interference sets, fading sets, parameter sets, means sets and result sets. Each module collects a large amount of information to form a reasonable knowledge system. The communication scenario includes satellites and ground stations. The ground stations and satellites contain channel information. The state of the channel is described by
parameters. The interference or fading of the channel will be determined according to the connection with the interference set and the fading set. Satellites are divided into multiple states, and each state can establish different rules and characteristics, as well as the influence on parameters, through the understanding of the current communication environment. The interference sets, the fading sets, the results sets, and the means sets are all collections of various knowledge, including corresponding characteristics and parameters.

2.2. Collaborative filtering with integrated path loss

In the current scenario, the concept of "user" is introduced, that is, every situation that currently requires decision-making is regarded as a "user". Specifically, the difference in the position of each satellite or ground station is described by latitude, longitude and altitude, and it is regarded as a different "user". And the input information such as the current received interference or fading is regarded as a different "item".

Calculate the user similarity according to the user-item preference matrix, and regard the user's preference for items as a matrix $R_{m \times n}$, as shown in Figure 1. Matrix row $m$ represents the total number of users, represented by the set $U=\{u_1, u_2, \ldots, u_m\}$, matrix column $n$ represents the total number of items, and the set $V=\{v_1, v_2, \ldots, v_n\}$. In the matrix, $s_{ij}$ represents the user $u_i$'s preference for the item $v_j$, and the value is 0 or 1, which means there is or not.

![Fig.1 User-item preference matrix](image)

| u_1 | v_1 | ... | v_j | ... | v_n |
|-----|-----|-----|-----|-----|-----|
| u_2 | s_{11} | s_{12} | ... | s_{1j} | ... | s_{1n} |
| ... | ... | ... | ... | ... | ... | ... |
| u_i | s_{i1} | s_{i2} | ... | s_{ij} | ... | s_{in} |
| ... | ... | ... | ... | ... | ... | ... |
| u_m | s_{m1} | s_{m2} | ... | s_{mj} | ... | s_{mn} |

Each row in the matrix is the user's preference vector for items, and the cosine similarity is used to calculate the cosine value of the angle between the user preference vectors to obtain the cosine similarity between users. As shown in formula (1).

$$sim_{ij} = \cos \theta = \frac{\overrightarrow{s_i} \cdot \overrightarrow{s_j}}{||\overrightarrow{s_i}|| ||\overrightarrow{s_j}||}$$

(1)

In the formula $\overrightarrow{s_i}$ represents the preference vector of user $u_i$, the row vector of $u_i$ in the matrix; $\overrightarrow{s_j}$ represents the preference vector of user $u_j$, the row vector of $u_j$ in the matrix.

In order to avoid dissimilar users from calculating the user similarity, resulting in an increase in the amount of calculation, the user-item preference matrix is transposed to obtain the user-item inverse lookup matrix. From the perspective of items, if users $u_i$ and $u_j$ do not have the same preference for all items, the similarity calculation between users can be avoided.

Next, considering the similar impact of distance loss on users, first introduce wireless communication free space path loss, as shown in formula (2).

$$P_r = P_t G_t G_r \left(\frac{c}{\lambda df}\right)^2$$

(2)

In the formula, $P_r$, $P_t$, $G_t$, $G_r$ represent receiving power, sending power, sending gain and receiving gain in turn, $c$ and $f$ represent the speed of light and the transmission frequency, and $d$ represents the distance. It can be seen that the influence of distance on the user is the same as $d^2$ is inversely proportional, and formula (3) is derived through normalization.
In the formula, $D_{sim}$ represents the influence factor of distance on user similarity, $d_{max}$ represents the maximum distance between all users in the current set, $d_{min}$ represents the minimum value, and $d_{in}$ represents the distance between the current two users to be calculated.

According to formula (1) and formula (3), the user similarity of the fusion path loss is obtained, as shown in formula (4).

$$sim(u_i, u_j) = sim_{ij} \times D_{sim}$$

Through the improved similarity, the recommendation degree of the items that the current user has not produced behavior is calculated, and the high recommendation degree is taken as the output result.

3. Simulation Results and Discussions

3.1. Knowledge graph

Based on a large amount of literature, this paper uses the neo4j library to establish a satellite-to-ground communication decision-making knowledge graph, as shown in Figure 2.

![Satellite-to-earth communication knowledge graph](image)

The satellite-to-ground communication decision-making knowledge map is generated according to the six modules in the figure. The subgraphs under each module are related to each other to form a complete knowledge graph.

3.2. Data set

According to the number of information in the knowledge map, 500 sets of user data are randomly generated. The 500 sets of data include preference information for 1 different item in the map and 500 sets of location information. At the same time, the satellite-to-ground communication will not be affected by all elements in the map, Set the user's preference items to no more than 1/3 of the total. Among them, 90% is used as the training set and 10% is used as the test set.

3.3. Algorithm comparison

The traditional user-based collaborative filtering (UB) and the integrated path loss collaborative filtering (UBP) are compared, and Precision and Recall are used to evaluate the effect, as shown in formulas (5) ~ (6).
\[ \text{Precision} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|} \]  
\[ \text{Recall} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|} \]

In the formula, \(R(u)\) is the recommendation list made to the user based on the user's behavior on the training set, and \(T(u)\) is the user's behavior list on the test set. The Precision indicates the proportion of user preferences in the predicted items to the total number of predictions, and the Recall indicates the total number of user preferences in the predicted items in the user's actual preferences, and the result is shown in Figure 3.

![Precision comparison chart](attachment:precision_chart.png)  
![Recall comparison chart](attachment:recall_chart.png)

Fig.3 Comparison result of precision and recall

It can be seen from Figure 3 that the collaborative filtering algorithm that integrates path loss (UBP) has a better precision and recall than the traditional user-based collaborative filtering algorithm (UB). Especially when the number of recommendations represented by the abscissa \(N\) is smaller, the difference between the accuracy and recall of the two algorithms is larger. This is because in the recommendation lists of the two algorithms, the traditional similarity is caused by the addition of the path loss factor. The priority recommended items calculated by the performance algorithm has changed, but the changes tend to change the priority order of the original recommended items. That is, as the number of recommendations \(N\) increases, the number of different items in the recommended lists of the two algorithms may not change as much as \(N\), but the relative order in the recommended lists changes. This rule is also in line with the purpose of algorithm improvement, to prevent items with a low recommendation from appearing at the top of the recommendation list.

3.4. Decision system comparison

In the context of satellite-to-ground communication, the decision-making system based on the knowledge graph (KG) is compared with the traditional decision-making system based on case-based reasoning (CB). It is evaluated in terms of accuracy, debugging, scalability and decoupling, as shown in the figure 4 shown.
It can be seen that the decision-making system based on the knowledge graph (KG) is better than the traditional decision-making system based on case-based reasoning (CB) in terms of accuracy, debugging and scalability. Decisions based on the knowledge graph do not require detailed definitions of cases, nor complex discussions of case similarity, but only need to adjust text similarity algorithms to obtain results, which is more accurate. Then the visual structure of the knowledge graph makes it easier to troubleshoot the situation of wrong output, but the system based on case-based reasoning cannot. The knowledge graph makes it easier to add new content through the structured input of various aspects of satellite-to-earth communication knowledge. The method of adding is also very simple. You only need to create node storage through the operation interface, but it is more complicated to add new content to the case library, especially when the structure of the current case is different, new case rules and algorithms need to be added to achieve it. In terms of decoupling, both are excellent. They are not highly coupled with other modules of the system and can be used with multiple algorithms or constraint rules at the same time.

4. Conclusion

In this paper, through the study of satellite-to-ground communication knowledge, a relevant knowledge map is established, through the abstraction of user concepts, a collaborative filtering algorithm is introduced, and a collaborative filtering algorithm integrating path loss is proposed. Experimental test results show that the improved algorithm is more suitable for the current simulation environment requirements, and at the same time the accuracy rate and recall rate are also improved.

The satellite-to-ground communication decision-making system based on the knowledge graph also has certain advancement and feasibility. In the future, considering incorporating more reasonable parameters and proposing a model closer to the real environment, I believe that artificial intelligence technology will have a broader application prospect in the field of satellite-to-ground communications.

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