Qos Web Service Design Based on Collaborative Filtering

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Abstract

In the process of web service recommendation, the prediction accuracy of Web Service missing Quality of Service (QoS) value will have an important impact on the rationality of service recommendation. Therefore, combined with spatiotemporal similarity perception, this paper proposes a new web service QoS collaborative filtering recommendation algorithm. This paper designs the framework of web service recommendation system from the perspective of QoS collaborative prediction, and gives the definition of related parameter set. Aiming at the problem that some services in the traditional Top-k algorithm are not similar to the target services, the spatial-temporal similarity perception combined with similar weight is used to predict the missing data to improve the prediction accuracy. In this paper, the calculation process of the algorithm is given through a simple example. The effectiveness of the algorithm is verified by the experimental results.

Keywords*: Web services, QoS, prediction accuracy, collaborative filtering.*

I. Introduction

With the development of computer technology and the continuous popularization of the network, more and more people are surrounded by the sea of information, recommendation system came into being in this context [1-2]. Recommender system is a system that provides personalized information for requesters. Compared with the traditional "one to many" search engine information service, it returns higher quality results and lower user participation. The use of recommender system can greatly reduce the cost of searching information. One of the important links in the process of recommender system is service selection. However, with the increase of the number of services on the network, there are a large number of Web services with the same or similar functions and behaviors but different quality of service (QoS), such as service response time, reliability, service price and so on. There are more and more services available for the same service request, so it is more and more important for service requesters to choose services that can not only meet the function but also meet the quality of service requirements. Therefore, considering QoS attributes in service selection has become a problem that can not be ignored [3].

Figure 1 shows an overview of QoS based service selection. A composite service consists of multiple abstract services, and each abstract service can be completed by a group of specific services with the same or similar functions. The purpose of QoS based service selection is to select candidate services from a group of specific services, so as to optimize the performance of composite services. However, due to the rapid increase in the number of candidate services, it is more and more common for web services to have incomplete QoS information [4-6]. In other words, for a large number of candidate services, a single user cannot call all of them. For example, there are 10 booking services deployed on the Internet, and a single user may have used only two or three. Based on this situation, before selecting services for users, it is necessary to predict the QoS of unused services [7]. Therefore, according to the existing records, the prediction of Web Service QoS becomes the key of service selection.

Table 1 is a simple example. The number in the table indicates the response time of the corresponding user calling the corresponding service, and null indicates that the corresponding user has not called the corresponding service,

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which is called lost data in this paper. Since there is no data of user U1 calling service S3 in the table, it is difficult to select the service with the shortest response time for user U1. Therefore, predicting missing data is very important for service selection.

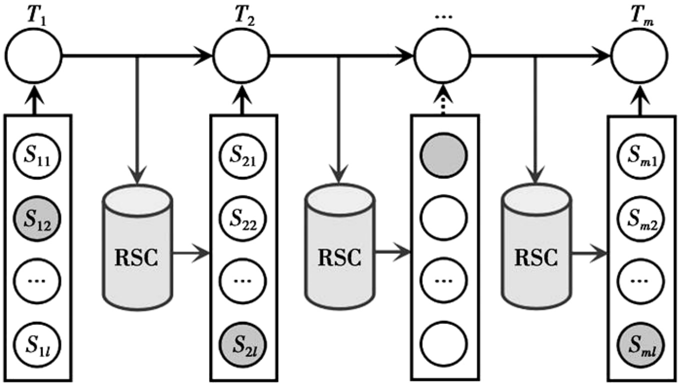

Fig 1: QoS based service selection

Tab 1: Service response time example

	S1	*S2*	*S3*
u1	0.4s	L6s	NULL
u2	2.6s	NULL	3.5s
u3	0.8s	0.9s	5.1s
u4	8s	3.0s	NULL

II. Collaborative filtering model

The idea of collaborative filtering (CF) is to use the preferences of groups with similar interests and common experience to infer the information that users may be interested in. Users respond to information to a certain extent (such as rating) to help other users screen information. Responses are not limited to information of interest, and the record of information of no interest is also very important. Collaborative filtering can be divided into evaluation filtering and group filtering. The latter has become one of the most important links in today's e-commerce operation. Its method is to recommend products to customers based on their historical purchasing behaviors and the purchasing behaviors of customers with similar purchasing behaviors. In short, it infers individual preferences with the help of the preferences of similar groups. At present, collaborative filtering has been widely used in various fields, in addition to e-commerce, in information retrieval, network personal video cabinet, personal bookshelf and other fields have its related applications.

A. User based collaborative filtering

User based collaborative filtering is to calculate the predicted value according to the user's information. Its basic idea is to calculate the relationship between users according to the existing records, find a group of users similar to the target user, and then calculate the predicted value of the QoS of the target user calling the target service based on the QoS information of these similar users calling the target service. Traditional collaborative filtering methods use Pearson correlation coefficient (PCC) to calculate the similarity between users or services. The calculation method is shown in formula (1) [8-10]:

$$\varphi_{u1,u2} = \frac{\sum_{s\in S}\left(r_{u1,S} - \bar{r}_{u1}\right)\left(r_{u2S} - \bar{r}_{u2}\right)}{\sqrt{\sum_{s\in S}\left(r_{u1,S} - \bar{r}_{u1}\right)^2}\sqrt{\sum_{s\in S}\left(r_{u2,S} - \bar{r}_{u2}\right)^2} \tag{1}$$

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After calculating the similarity between users, a group of users with the highest similarity can be selected as the prediction reference for the target users, which is called similar neighbor users. Based on the existing records of similar neighbors calling the target service, the final prediction result can be calculated. The calculation method is shown in formula (2)

$$p_u = \bar{r}_u + \frac{\sum_{u1 \in U} \varphi_{u1,u} \times \left(r_{u1,S} - \bar{r}_{u1} \right)}{\sum_{u2 \in U} \varphi_{u2,u}} \tag{2}$$

B. Service based collaborative filtering

Item based collaborative filtering is to calculate the predicted value according to the service information. Its basic idea is to calculate the relationship between services according to the existing records, find a group of services similar to the target service, and then calculate the predicted value of QoS for the target user to call the target service based on the QoS value of these services called by the target user. Similarly, in the traditional collaborative filtering algorithm, the similarity between services is also calculated by PCC, and the calculation method is shown in formula (3):

$$\varphi_{s1,s2} = \frac{\sum_{u \in U} \left(r_{u,s1} - \bar{r}_{s1} \right)\left(r_{u,s2} - \bar{r}_{s2} \right)}{\sqrt{\sum_{u \in U} \left(r_{u,s1} - \bar{r}_{s1} \right)^2} \sqrt{\sum_{s \in S} \left(r_{u,s2} - \bar{r}_{s2} \right)^2}} \tag{3}$$

After calculating the similarity between services, we can select a group of services with the highest similarity for the target service as the prediction reference, which is called similar neighbor service. Based on the existing records of similar neighbor service called by the target user, the final prediction result can be calculated. The calculation method is shown in formula (4):

$$p_s = \bar{r}_s + \frac{\sum_{s1 \in S} \varphi_{s1,s} \times \left(r_{u,s1} - \bar{r}_{s1} \right)}{\sum_{s2 \in S} \varphi_{s2,s}} \tag{4}$$

C. Comprehensive collaborative filtering

As the name suggests, collaborative filtering that integrates users and services is to comprehensively consider the prediction results of user based collaborative filtering method and service based collaborative filtering method. Generally, the weighted average of the prediction results of the two methods is taken as the prediction result. The calculation method is shown in formula (5):

$$p_{us} = \frac{p_u + p_s}{2} \tag{5}$$

III. Modeling and experimental analysis

A. Modeling

How to get context information accurately is the basis of application context. Generally, context information is acquired in the data acquisition phase of the system. The main ways of context acquisition are: display acquisition, implicit acquisition and reasoning acquisition.

(1) Explicit acquisition: as the name suggests, it directly obtains the relevant context information, and the acquisition methods mainly include user active setting, user inquiry and physical device awareness.

(2) Implicit acquisition: indirect acquisition of relevant context information, mainly by analyzing the surrounding environment and existing data.

(3) Inference acquisition: using statistical methods or data mining technology to infer relevant context information.

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Among them, explicit context information is the most accurate, but it is difficult to obtain most meaningful context information only by using explicit context information.

Different context information has different value for the same application field. For the same field, some context information has great influence on recommendation, while others have little influence on recommendation. Therefore, before recommending to users, it is very important to identify and obtain the context that has a great impact on the recommendation. We call this context information effective context information. This paper uses Bayesian network iterative filtering method to filter the context noise in recommendation system, and proposes a method based on support vector machine to dynamically identify the best context. This paper uses data mining technology to decide which context information should be introduced into the recommendation system, and proposes that experts select the initial context for specific applications. In order to enable users to explicitly specify the information they are concerned about, the system should provide rules that users can input.

The heterogeneity and dynamism of context information lead to different ways of expression. It is another important problem to establish a unified representation model for these huge, wide-ranging and complex context information. However, this is not a simple task.

Generally, there are six common context modeling methods based on data structure: machine learning model, ontology based model, logic based model, object-oriented model, graph model, tag model and key value model. Among them, machine learning model can solve the problem of data overload, it uses machine learning algorithm to build context model; ontology based model can effectively describe the context and its relationship, which is convenient for computer processing. Based on logical model, context information is defined as rule, expression or fact, and reasoning is carried out on this basis. As the name suggests, the object-oriented model uses the idea of object-oriented to build the context model, providing a standard interface to access the context information, and the details of the context are encapsulated in the object. Graph model is suitable for building data structure between contexts. This model uses graph to build context model and get E-R graph of context. Tag model uses hierarchical data structure to organize tag attributes and content; key value model uses keys to represent environment variables and values to represent actual context data, which is simple, but can not represent the context of complex data structure.

In real life, the QoS value of Web services is closely related to the bad environment of Web services and users. For example, a web service with poor network conditions will have a long response time for all users. This is because the network of Web services becomes the main factor determining the response time under this condition. Although, in general, the QoS value of Web services is determined by both users and services, when one of them is "under poor conditions", the QoS value tends to be restricted by the "under poor conditions". For example, after calculation, the response time of general service is 1s, while the response time of service SA is 50s, which is much longer than that of general service. At this time, we call service Sa "special" service.

There is no clear definition of service or user condition, but it can be obtained from context information (QoS data matrix information of user calling service). In this paper, "average value of service" is used as a measure to determine service conditions, and "average value of users" is used as a measure to determine user conditions. "Average value of service" refers to the average value of QoS that a service is called by all users who call it. In terms of response time, the smaller the average value of service, the shorter the average response time of service, and the larger the average value of service, the longer the average response time of service. Because the average response time is the average value of the response time of the same kind of users calling the service, it has little relationship with the users and mainly reflects the conditions of the service itself. The large average response time is probably caused by some characteristics of the service itself (such as the poor network where the service is located, the large amount of data that the service needs to process, etc.), and it has nothing to do with which user calls it. Therefore, the "average value of service" is selected to judge the quality of service conditions.

Similarly, "average value of users" refers to the average value of QoS obtained by a user invoking a set of services. It has little relationship with the service called, mainly reflects the user's own conditions, and can determine the quality of the user's conditions. According to the above theory, we divide users and services into two categories: special user class and normal user class, special service class and normal service class. Specific definitions are as follows:

1) "Special user" category: it is composed of Nu users with the largest average value, expressed by up;

2) General user class: it includes all users that are not in the "special user class", which is represented by UN;

3) "Special service" category: it is composed of NS services with the largest average service, expressed by Sp;

4) General service class: contains all services that do not belong to the "special service" class, represented by SN.

It is not difficult to understand that, on the one hand, the QoS related to "special users" (special services) is mainly determined by the corresponding "special users" (special services), and is little affected by other information; on the other hand, the existence of QoS information related to "special users" (special services) can not improve the QoS of ordinary users calling ordinary services The accuracy of prediction may even have a negative impact on prediction, for example, when "special users" are selected as similar neighbors of ordinary users. Therefore, we divide the matrix into two parts: "special matrix" and purified matrix. The "special matrix" contains only the QoS information related to "special users" or "special services", which is used to predict the QoS of "special users" or "special services"; the purified matrix does not contain the information related to "special users" and "special services", which is used to predict the QoS of ordinary users calling ordinary services.

Area is another important factor that affects QoS. As shown in Figure 2, service a in the United States can be called by users in multiple regions such as the United Kingdom, Japan, India, etc. It may be that the network failure from the United States to Japan caused by the recent earthquake in Japan leads to a long response time for users in Japan to call service A. it may also be that due to the more complete network facilities from the United Kingdom to the United States, the impact of service a from users in the United Kingdom should be much faster than that in other regions. We call the services that show different QoS for different regions as region sensitive services, such as service A.

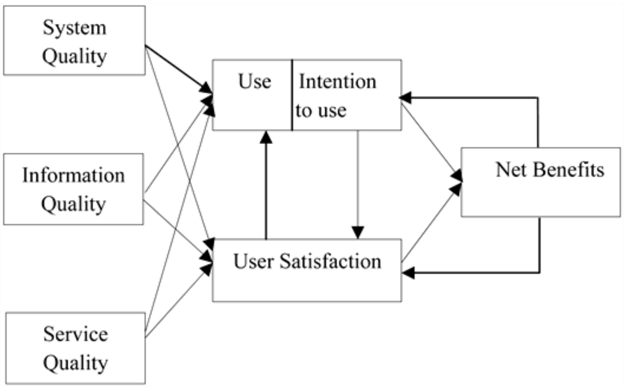

Fig 2: Examples of users in different regions calling the same service

B. Optimization effect analysis

The experiment in this paper is based on real data sets and uses the normalized mean absolute error (nmean) as a measure. The data set is a standard database set, which is a 150 × 100 user service matrix. The data items in the matrix are two-dimensional vectors representing response time and throughput respectively. In the experiment, the 150 × 100 matrix is divided into two parts according to users, in which n rows are used as the training matrix and the remaining (150-n) rows are used as the test matrix. The user in the test matrix is the target user. Then, the training matrix density is randomly sparse to simulate the real data environment. In order to reduce the error, each experiment was run 50 times and the average value was calculated.

We use K to represent the number of selected similar neighbors, density to represent the data density of the sparse training matrix, t to represent the number of rows of the training matrix, and G to represent the total number of services that the test user has called. The number of "special services" and "special users", namely Nu and ns, directly affects the optimization effect. If the number set is too small, the purpose of classifying "special services" cannot be achieved; if the number set is too large, ordinary services (users) may be classified into "special services" (special users), which will have a negative impact on the prediction. Because "special service" has a great influence on user based collaborative filtering, "special user" has a great influence on service-based collaborative filtering algorithm. Therefore, in order to study the influence of Nu and ns on the optimization effect, this paper records the accuracy changes of service-based and user based optimization algorithms when Nu and NS change from 0 to 10.

In the experiment, we set K = 10, density = 0.1, t = 100, g = 10 / 20 / 30. The results are shown in Figure 3. Among them, Fig. 3 (1-2) is the experimental result for nu, Fig. 3 (3-4) is the experimental result for NS, Fig. 3 (1-3) is the experimental result for response time matrix, and Fig. 3 (3-4) is the experimental result for throughput matrix. As can be seen from Fig. 3 (1-2), whether for response time matrix or throughput matrix, when Nu is less than 9, the prediction accuracy increases with the increase of Nu, when Nu is greater than 9, the prediction accuracy decreases rapidly with the increase of Nu, and when Nu = 9, the prediction accuracy is the highest. This is because, when Nu is less than the optimal value of 9, a small number of "special users" are classified as ordinary users, and with the increase of Nu, these "special users" are correctly classified as "special users", so the accuracy increases; when Nu is greater than the optimal value of 9, with the increase of Nu, more and more ordinary users are wrongly classified as "special users", so the accuracy increases.

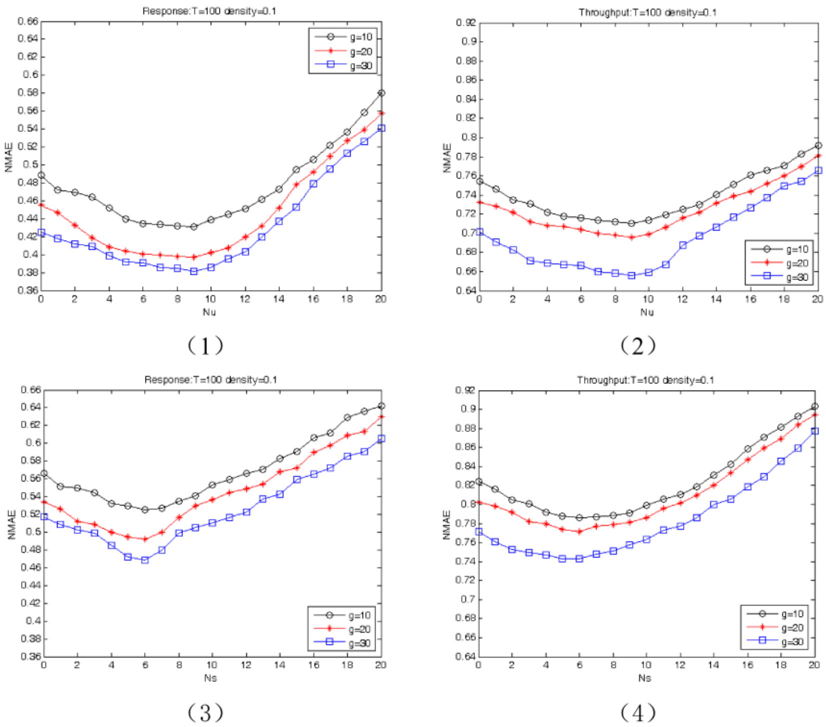

Fig 3: Influence of Nu and Ns on optimization effect

The error of umean in predicting the QoS of ordinary users is large, which leads to the rapid decrease of accuracy. Similar conclusions can be drawn from Figure 3 (3-4). The difference is that when Ns = 6, the prediction accuracy is the highest. As a threshold to control sensitive services in service area, it is self-evident that it is important to select sensitive services in service area. To investigate errors! Reference source not found. We recorded the experimental data on the influence of prediction accuracy. In the range of 0-10, the accuracy of service-based and user based optimization algorithms changes. In the experiment, we set K = 10, density = 0.1, t = 100, g = 10 / 20 / 30, Nu = 9, Ns = 6.

The results are shown in Figure 4. Among them, FIG. 4 (1-2) is the experimental result of the service based collaborative filtering optimization algorithm, FIG. 4 (3-4) is the experimental result of the user based collaborative filtering optimization algorithm, FIG. 4 (1-3) is the experimental result of the response time matrix, and Fig. 4 (3-4) is the experimental result of the throughput matrix. In order to study the effect of the optimization

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method, we implement the following four web service QoS prediction algorithms:

a) The traditional collaborative filtering method based on users is called UPCC;

b) The traditional collaborative filtering method based on service is IPCC;

c) We call it adjusted UPCC based on context;

d) We call it adjusted IPCC based on context.

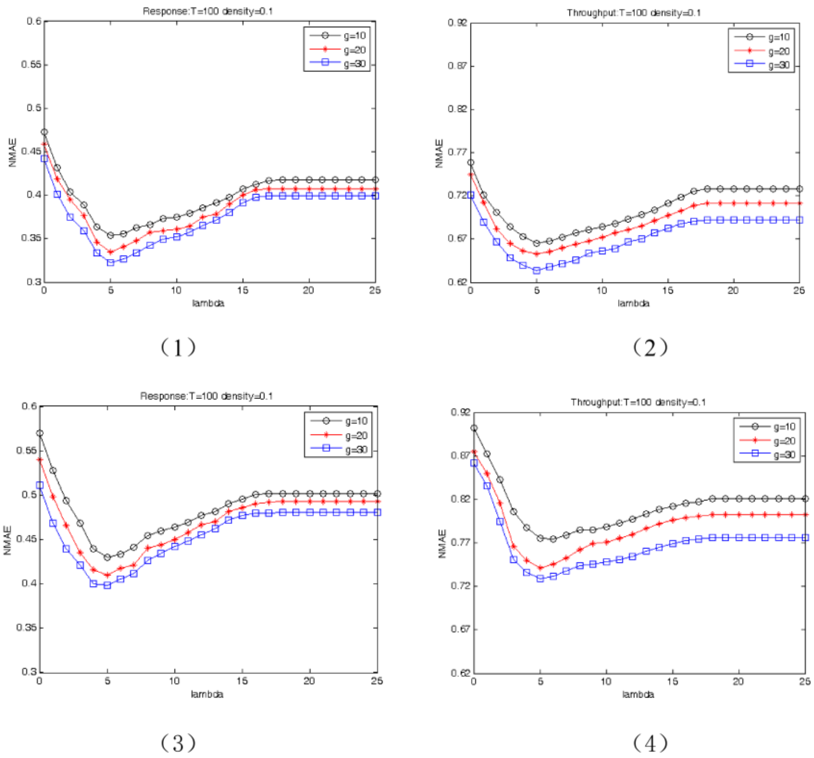

Fig 4: Analysis of the influence of λ on optimization effect

The four methods are based on real data sets, and the prediction accuracy is measured by nmae. In the experiment, we set K = 10, t = 100, density = 0.1, nu = 9, ns = 6.

The results are shown in Figure 5. Figure 5 (1-2) shows the change of prediction accuracy of IPCC and adjusted IPCC based on context with G, figure 5 (3-4) shows the change of prediction accuracy of UPCC and adjusted UPCC based on context with G, figure 5 (1) (3) is the experimental result of response time matrix, and figure 5 (2-4) is the experimental result of throughput matrix. As can be seen from Figure 4, in all cases, the context based optimization method is more accurate than the traditional collaborative filtering method. That is to say, optimizing the collaborative filtering method based on context information can improve the accuracy of prediction. At the same time, we can also find that when G is less than 20, the prediction accuracy increases rapidly with the increase of G; when G is more than 20, the prediction accuracy increases very little with the increase of G. This is because when G is small, G is the main limiting condition of the prediction accuracy, while when G is large, the prediction accuracy is mainly limited by the matrix density.

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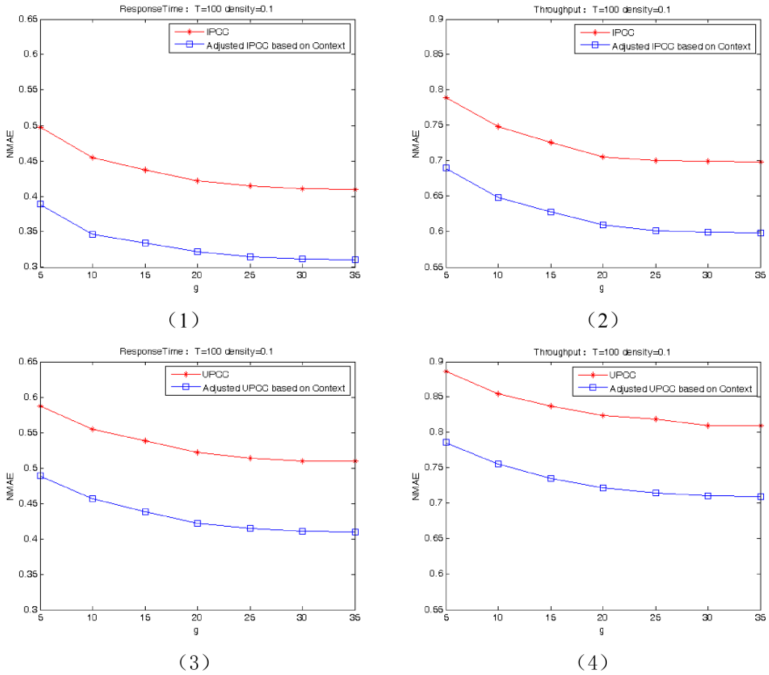

Fig 5: Optimization effect

V. Conclusion

This paper mainly describes the optimization of collaborative filtering algorithm based on collaborative filtering information. Firstly, the definition of collaborative filtering, the acquisition of collaborative filtering, the modeling of collaborative filtering and the research status of collaborative filtering are introduced. Secondly, the modeling method based on collaborative filtering information in the field of Web prediction and the optimization method of collaborative filtering algorithm based on the model are analyzed. Finally, the optimization algorithm is implemented based on the real data set, and the effect of the optimization algorithm and the influence of the parameters in the modeling on the accuracy of the optimization algorithm are analyzed.

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