AN ARTIFICIAL INTELLIGENCE TECHNIQUE FOR EXPLORATED SEARCHABLE QUERY PROCESSING

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***Abstract*—** Exploratory search is an increasingly imperative movement for Web searchers. Be that as it may, the ebb and flow seek framework cannot give adequate help to exploratory inquiry. In this manner, we made inside and out investigation for exploratory pursuit procedures and found that there are a ton of hunt objective move marvels in exploratory inquiry. In light of this reality, we have planned another inquiry proposal technique to help exploratory pursuit. Right off the bat, as per the social qualities of searchers in the inquiry objective move forms, every one of the questions submitted in the pursuit objective move forms are extricated from web crawler logs utilizing AI. And after that we have utilized the inquiries to assemble a pursuit objective move diagram; at long last, the arbitrary walk calculation is utilized to get the inquiry suggestions in the hunt objective move chart. Likewise, we showed the viability of the strategy for exploratory pursuit by contrasting examinations and alternate strategies.

***Index Terms*—** *Exploration Search, Query Recommendation, Artificial Intelligence.*

I. INTRODUCTION

Exploratory search is an increasingly important activity yet challenging for Web searchers. In exploratory search, the searcher is unfamiliar with their problem domain, unsures about the ways to achieve their goal, or lacks a well-defined goal. To support exploratory search, the search system is required not only to provide accurate search results, but also to help searchers explore related and novel aspects. Therefore, exploratory search system needs an effective query recommendation method to re-solve this problem. However, the current query recommendation methods mainly focus on optimizing users' current query which is far away from satisfying users' information needs of the whole search session. To support exploratory search, we observed and analyzed the search logs of exploratory search process performed by different users, and we found that there are a lot of search goal shift phenomena in exploratory search. As the following example: A Chinese university student attends a birthday party organized by a French student, and he wants to choose a suit-able birthday gift, which is a typical exploratory search task. Because the Chinese student only got some very vague goals, such as

Object: a gift not a normal thing

Applicable occasions: birthday party

Basic features: French favorite items

Budget: 200 RMB or so.

Based on these conditions, the student used the key words “French people like flowers” for the query; explored “flowers” which is the most popular gift. He felt using flowers as a birthday gift doesn’t feature after clicking many links of search results. And the search results mentioned that French people are very fond of drinking wine. So, he changed his idea and felt that “wine” may be more appropriate as a gift for the birthday party. So, the user used “French wine” as a key word and query “red wine” as new search goal to explore. Using the search results about the “French wine brand” and “French wine prices”, the student figured out French wine prices are expensive far beyond his budget. Obviously “red wine” is not a suitable search goal either. At the same time, he thought, “arts and crafts” may be more appropriate. Then he used “handicrafts”, “Chinese arts and crafts” as key words to query on the "arts and crafts" which is a new search goal, and eventually found hopeful gift to the end of the search task. From the example, it’s clear that the user's search goal shifts from the “flowers” to “red wine” and then from the “wine” to “arts and crafts”. And the search goal shifts precisely reflect the user’s exploratory behaviors and needs. Therefore, we based on the "search goal shift" de-signed a new recommendation method to support exploratory search. Firstly, according to the user’s behavioral characteristics in the search goal shift process, we extracted all queries during search goal shift processes from search logs; then we used the queries to construct a search goal shift graph; finally, we recommended other goals related to the current goals using the search goal shift graph. In addition, we have designed a query recommendation test method, by which we can compare our recommendation method with the other methods. And the experimental results showed that the recommendation method we designed can significantly shorten the search.

II. RELATED WORK

A. Query Recommendation

Most of the query recommendation techniques are using similarity measures between queries by query terms, clicked documents, or sequences of queries in sessions. Baez Yates et al.[1] [2] extracted query-clicked URL/doc bipartite graphs using search logs to find query recommendations. Craswell and Szummer [3] also used the query-click graph to find related documents and queries. Mei et al. [4] presented a “Hitting Time” algorithm to find related queries using the query-click graph. Cao et al. [5] tried to understand user's context which include multiple information including age, gender, username, IP, tools etc. and also previous queries in a query session in order to suggest new queries. Boldi et al. [6] proposed a query-flow graph which represents the latent querying behavior contained in a query log.

B. Exploratory Search

In the past 30 years, many scholars have made in-depth study of the search process of exploratory search behavior. In 1989, Dr. Bates M J proposed Berry picking model [7] that the user's search direction and the desired result will constantly change with the search process changing. In 1991, Kuhlthau C C proposed that information retrieval process includes starting, selection, exploration, collection and ending six stages [8]. In 1995, Byström K and Järvelin K used the methods of logs and questionnaires to analyze the relationship with search complexity of the task, type of information, information channels and resources [9]. In 2006, Marchionini G proposed exploratory search [10]. Recently, exploratory search research focuses on the characteristics of the exploratory search process and the different types of support needed to help people make exploratory searches [1]. Someone tries to provide a query preview control by allowing users to take nodes and record the results [11] so that they can view the distribution of newly-retrieved and retrieved documents before running the query [12]. Some research efforts focus on traditional search techniques such as query suggestions, aspects and information classification. For example, Hassan Awadallah et al. [13] constructed a method of automatically identifying and recommending tasks that allow searchers to explore and complete complex search tasks, Sun et al. [14] proposed a topic-oriented query for exploratory search method, Ksikes et al. [15] designed an exploratory faceted search system, Zhang et al. [16] grouped the relationships between entities into a virtual-generated hierarchical clustering to an effective leader to explore and discover. Other attempts have been made to design and research visual search interfaces and interactive user modeling to support exploratory search tasks. For example, Bron et al. [17] proposed an auxiliary exploratory search interface to support media research; Bespinyowong et al [18] designed exploratory data exploratory ranking interface; Peltonen et al [19] used a negative feedback search intent radar interface to help users conduct exploratory search. All these previous methods focus on refining user requirements, showing several facets helping users refine their requirement and find their desired information. But they cannot satisfy such user needs as finding some novel search goals when users are losing the interests of current search goal.

III. EXISTING SYSTEM

The current query recommendation methods mainly focus on optimizing users’ current query which is far away from satisfying users’ information needs of the whole search session. To support exploratory search, we observed and analyzed the search logs of exploratory search process performed by different users, and we found that there are a lot of search goal shift phenomena in exploratory search. Most of the query recommendation techniques are using similarity measures between queries by query terms, clicked documents, or sequences of queries in sessions. In existing system, they used extracted query-clicked URL/doc bipartite graphs using search logs to find query recommendations

A. Disadvantages

All these previous methods focus on refining user requirements, showing several facets helping users refine their requirement and find their desired information. But they cannot satisfy such user needs as finding some novel search goals when users are losing the interests of current search goal.

IV. IDENTIFICATION ALGORITHM

In this section, we used the logistic regression algorithm to transform the identification of the search goal shift into the binary classification problem. The core idea of logistic regression algorithm is using sigmoid function to convert classification problem into a probability estimate. If a feature value is inputted into the sigmoid function and the calculated value is greater than a certain threshold, the query pair is search goal shift query pair. Otherwise less than or equal to the threshold, the query pair is a normal query pair. T (true) indicates that the goal shift query pair, F (false) indicates the normal query pair. The model target is to find the function f,

F: D {T, F}

where D= {x1, w1, xi, wi, …, xn, wn}, x is the input feature values vector. w is the coefficients vector. The probability of search goal shift query pair is:

$$p(y{=}T|X;W)=\frac{1}{e^{-w7x}}$$

$$P(y=F|x,w)=1-P(y=T|x;w)=1-\frac{1}{1+e^{-w7x}}$$

The Function f is:

$$f(P(D))=\begin{cases}T, P(D) > threshold \\ F, p(D) \leq threshold\end{cases}$$

According to the derivation above, the process of get-ting model (function f) is a finding process for best-fit parameters, which is the coefficient of each feature value. For parameter vector w, we use maximum likelihood estimation algorithm to obtain.

Let $h_w(x) = g(w^3x) = \frac{1}{1+e^{-w^3}x}$; g(z)=$\frac{1}{1+e^{-z}}$ $then;$

$$\text{P(D)=P}(y|x,w) = \left(h_w(X)\right)^3(1-h_w(x))^{1-y}$$

According to (18), we can get the maximum likelihood function L (w | x, y) and the optimization function l (w).

l(w)=log$(L(w|x,y))$

$$=\sum_{i=i}^{m}(y^i logh_w(x^i)-(1-y^i)\log(1-h_w(x^i))$$

Finally, we can use gradient descent optimization meth-od to obtain update way of w:

w:=w+α·x(g(w·x)-y)

Specific recognition algorithm as follows:

Algorithm 1 ExIdentifyGSPair

Input: rate, x, y

// rate is learning rate

// X is feature value vector

// Y the artificial identification results

Output: w

// parameter vector

$w = initialize\_value;$

$For\ every\ x_i \epsilon X, y_i \epsilon\ Y\ Do$

$p = {\exp(w \cdot x_i)}\Big/{(1+\exp(w \cdot x_i))}$

$If\ P >$threshold then

$Predict\ true;$

$Else$

$Predict\ false;$

$End\ If$

$If\ Y_i == 1\ Then$

// It indicates that the current query pair is

// the goal shift query pair

$w = w + (1-p) \cdot x_i \cdot rate$

$Else$

$w = w - P \cdot x_i \cdot rate$

$End\ If$

$End\ For$

Computing edge Wight: For two goals (nodes) Ni, Nj linked by an edge, the edge weight w (Ni, Nj) represents the strength of their association. To measure the association between pairs of search goals we used the Normalized Pointwise Mutual Information described in section 5.1.2.

$$Weight(N_i, N_j) = \frac{\sum_{q_i \epsilon N_i}\sum_{q_i \epsilon N_i}\ln\frac{p(q_i,q_j)}{p(q_i)\times p(q_{j)}}}{-\sum_{q_i \epsilon N_i}\sum_{q_j \epsilon N_j}\ln p(q_i,q_j)}$$

Where,$p(q_i) = {C_q}\Big/{Q'}$ $p(t_i,t_j = {C_{q_{i,}q_j}}\Big/{Q'^{Q}})$ is the number of all queries in the dataset, is the number of query qi in the dataset, is the number of search goal shift query pairs {qiqj} in the dataset. Specific recognition algorithm as follows:

Algorithm 2 ExBuildSGSGraph

Input: P

// P is the goal shift query pair set

Output: V, E

// V is the set of nodes E is the set of edges

$A = getAllqueries(p);$

// put all queries submitted during search goal shifts in to a

// query set A

$For\ q\epsilon\ A\quad Do$

$For\ q'\epsilon\ A\quad Do$

$v = new\ Node(q)$

$V.add(v)\qquad //add\ \ a\ new\ node$

$If\ SameGoal(q,q')Then$

$query_{listv}.add(q')$

$End\ If$

$End\ For$

$End\ for$

$For\ v \in V\ \ Do$

$For\ v'\ \in\ V\ Do$

$query\_list_v = getQueryList(v)$

$query\_list_{v'} = grtQueryList(v')$

$If\ ExistSGS\ (p, query\_list_v, query\_list_{v'}) Then$

$e_{v,v'=1}$

$w(v, v') = NMI(v, v')\ //set\ weight$

$End\ If$

$End\ For$

$End\ For$

V. PROPOSED SYSTEM

This paper presents the search goal shifts precisely reflect the user’s exploratory behaviors and needs. Therefore, we based on the "search goal shift" de-signed a new recommendation method to support exploratory search. Firstly, according to the user’s behavior-al characteristics in the search goal shift process, we extracted all queries during search goal shift processes from search logs; then we used the queries to construct a search goal shift graph; finally, we recommended other goals related to the current goals using the search goal shift graph. Based on the basic framework of the search goal shift graph, exploratory query recommendation method mainly consists of two parts, offline and online. Our final goal is to provide query recommendations for users, the process of “identifying search goal shift” is to identify all search goal shift query pairs from the search engine logs and use them to compose of the candidate set.

A. Motivation:

In order to make a more accurate analysis for the behavioral characteristics of exploratory search, we firstly de-signed four search tasks with the characteristics of the exploratory search according to the literature [20] and organized 30 volunteers to make actual searches for these exploratory search tasks. Specific tasks as follows:

1)Supposing you are a reporter and asked to write an article about information security, the article needs to include a basic introduction theme, as well as significant information security incidents which happened in the past. And describe how the security of information affects people's daily lives from different views. Finally focus on the ways of preventing information leaks and improving information security

2) Assuming you have a family of four and a monthly household income of 20,000 RMB, and you are ready to buy a house in Beijing. Now you need to write a purchase plan to help families make decisions. The plan includes each property’s basic in-formation outlined in items such as: location, size and price. Then it should also describe periphery of education, health care and property management information. Finally, it could compare ad-vantages and disadvantages of each project analyzed.

3) Supposing you have a 40-year-old, type 2 diabetic male relative who wants to lose weight. But he can only spend three hours a day exercising due to his busy work. He is not familiar with network technology, so he wants you to help him develop a diet and exercise plan. This plan should not only include the effects, but also mention that it may bring risks and the way of how to monitor the risks.

4) The examples mentioned in the preamble, let's say you are a Chinese university student and pre-paring for a birthday party organized by the French students. How to choose a suitable birth-day gift? The task requires you to select the strategy and selection reason or exclusion reason for each item. For each search task we required volunteers to complete in 1 to 2 hours. And in each task, we obtained the results at the same time also collected each volunteer's search logs to analyze. We adopted the following concepts and definitions for analysis processes.

B. Related concepts:

1. Query topic: The query topic is a category used to describe the structure of the query information.

2. Hierarchy of the query topics: We divided the hierarchy of query topics for all the users by the two-tier topic model.

we define all the topics contained in the upper layer as higher-level topics and define all the topics we include in the second layer as lower-level topics in this model. The lower-level topic represents common cooccurrence patterns (correlations) between words in sentences. The higher-level represents common co-occurrence patterns (correlations) between lower-level topics in documents. For example, “star bucks” and “Schultz (Starbucks creators)” often appear in the same sentence, so they are often clustered into the same lower-level topic (coffee). “Carrefour” and “supermarket” are also clustered into the same lower-level topic (retail) because they often appear in the same sentence. The statements that contain “Starbucks” and “Schultz” and statements that contain “Carrefour” and “supermarket” often appear in the business documents, so lower-level topics “coffee” and “retail” are often clustered into the higher-level topic “business”.

3. The relationship between the query topics: According to the two-tier topic model, we can get the relationship between the query topics shown in Table 1.

Table 1 The relationship between query topics

The relationship between query topics

$Sim_{L-topic}(q, q')$	$Sim_{tf-topic}(q, q')$	relationship
>threshold η	=threshold φ	$T_i = T_{q'}$ topic consistency
>threshold η	<threshold φ	$T_q \, ? \, T_{q'}$ topic coherence
<threshold η	<threshold φ	T_q topic change

B. Related definitions:

1. Search goal: An atomic information need is reflected through a query query or more queries. That is, two consecutive queries in the same session, and if they are similar to each other based on a given threshold, they belong to the same search goal. The form is de-scribed as:

1 Sim (q, q') > threshold

Same goal (q, q') =

0Sim (q, q') < threshold θ

2. Search goal shift: In the exploratory search process, when the user isn't interested in the current search goal and submits a query q' for the next step search. If the query q and the query q' do not belong to the same search goal but they are topically-coherent, the search process between the two quires is defined as the search goal shift. The query q and the query q' are called the search goal shift query pair. Its formal description is q → q'.

VI. SYSTEM ARCHITECTURE

Based on the basic framework of the search goal shift graph, exploratory query recommendation method mainly consists of two parts, offline and online.

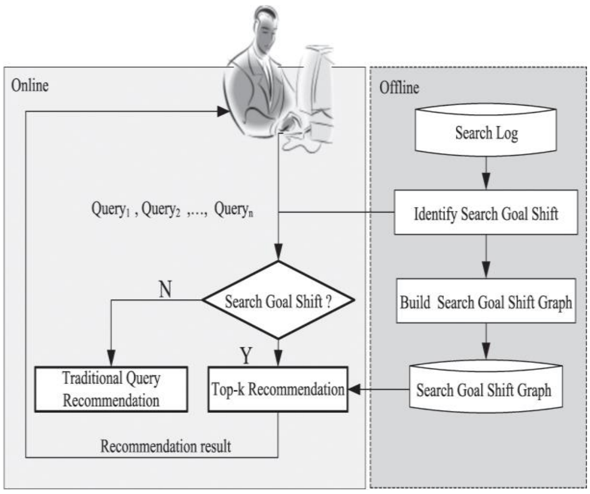

Fig1: System Architecture

A. Offline Part

Offline part mainly includes two major steps, the search goal shift identification and the search goal shift graph building. In the offline part, we manually annotate the search goal shift in some users' search session, then use machine learning to convert inefficient manual identification process into efficient AI calculation. Finally, we use all queries submitted during search goal shifts to construct a search goal shift graph.

B. Online Part

Online part also contains two steps, user's search behavior judgment and top-k recommend. In the online part, we use the identification model which is trained from the offline part to judge whether users' search behaviors belong to "search goal shift", then we use a random walk algorithm to find the top-k most relevant search queries from the search goal shift graph as a result of recommendation. Finally, based on the query on the different positions in the session, we compared search goal shift query pairs with normal query pairs on the average rank of clicked URLS. The comparison results are shown in Fig.

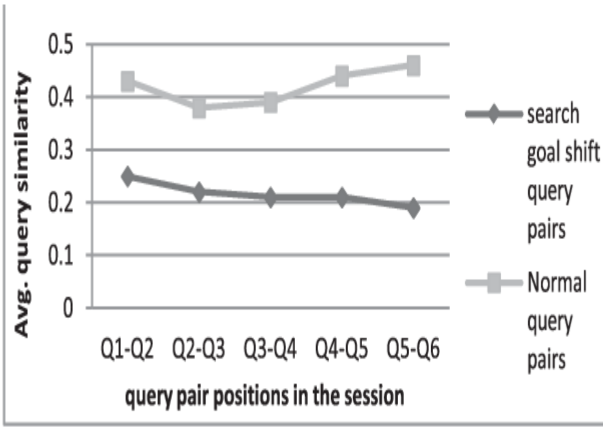

Fig2: Comparison result of rank of the clicks

Fig. shows the average rank of clicked URLS for search goal shift query pairs is less than the average rank of clicked URLS for normal query pairs. All differences reported in Fig. 8 are statically significant at the 0.05 level according to a two-tailed t-test. This confirms that the rank of clicked URLS can be used to distinguish between the search goal shift query pair and the normal query pair.

VII. EXPERIMENT

A. Experimental Data:

We choose search engine query logs of Sogou Company in June 2008 as base experimental data. The log data format is access time \t user ID \t [search words] \t the URL's ranking in returned results \t sequence number of use clicked\t URL user clicked. In the experimental data pre-processing stage, we used the approach designed in [21] to extract 5000 exploratory search sessions from the search engine log, totally 50,616 queries.

VIII. EVALUATION OF THE IDENTIFICATION ALGORITHM

Ground Truth for test: We used the method of artificial identification to select 10000 query pairs from the 5000 search sessions. The choice criterion is to extract two query pairs from each session, a search goal shift query pair and a normal query pair. And then we randomly selected a certain number of query pairs and used them to compose of a dataset for test. According to the observed result in section 3 (Fig. 3), the proportion of search goal shift query pairs in the dataset is 52%, and these search goal shift query pairs were considered to be ground truth. For this proportion, the maximal number of query pairs in the dataset for test is limited to 9000 pairs.

A. Baseline method

We compared logistic regression algorithm adopted by us (LR) with the following two the-state-of-art identification algorithms

1) Support Vector Machine (polynomial kenel) [31]

2) Decision tree (C5.0) [32].

B. Evaluation Metrics

1) *Precision*: It indicates the proportion of the actual positive examples in positive examples set.

$$precision = \frac{TP}{TP + FP} \times 100\%$$

2) *Error rate*: It indicates the proportion of misclassified.

$$error = \frac{FP + FN}{P + N} \times 100\%$$

3) *Recall*: It is a measure of coverage, metrics of how many positive cases in positive examples.

$$recall = \frac{TP}{TP + FN} \times 100\%$$

Where TP represents the number of correctly classified as positive examples. FP represents the number of incorrectly classified as positive examples. TN indicates the number is correctly classified as a negative example. FN represents the number of incorrectly classified as negative example.

Experimental results and analysis:

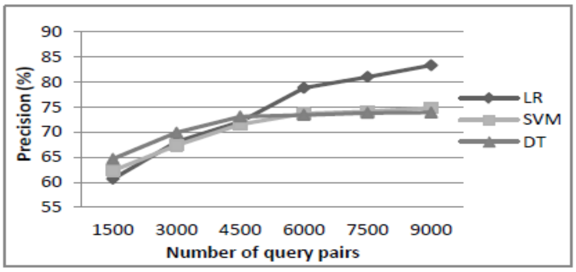

Fig. 3. Comparison result of precision. We split each set to 4/5 training and 1/5 testing

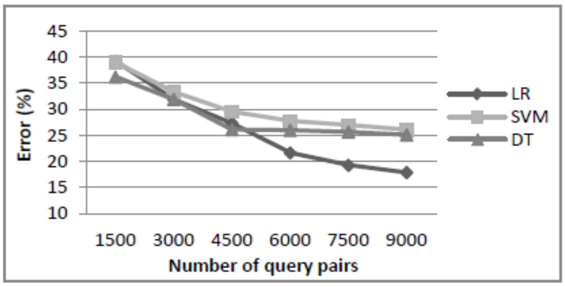

Fig. 4 Comparison result of error rate. We split each set to 4/5 training and 1/5 testing

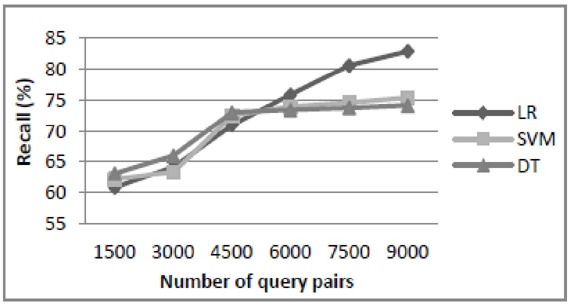

Fig. 5 Comparison result of recall. We split each set to 4/5 training and 1/5 testing

VIII. RESULT

A. Comparison of the recommendation results

Ground Truth for test: We retrieved the 5,000-search goal shift query pairs from section 7.2 and selected the first query in each query pair (the user first submitted) and counted the number of occurrences. And then we selected the top 1000 queries as the test set, and finally collected the ground truth data for each selected query. Given a query q, we extracted all queries q' (q and q' are composed of a search goal shift query pair) from the 5000-search goal shift query pairs obtained in section 7.2 and taked them as ground truth data of q, such as.} '...,','{) (21*nqqqqGT*

B. Baseline method

We compared our design recommendation method (GSES) with the following two methods that also support exploratory search based on query recommendation (mentioned in section 2.2).

1) Topic-Oriented Exploratory Search (TOES): TOES is a query recommdation method based on the topic se-mantic association graph. The topic semantic association graph has been built by hyperlinks on the Inter-net [14].

2) Exploratory Search Based on Search Task (STES). STES is a query recommdation method based on the task graph. The task graph is built by different search tasks that have been identified based on entities and syntactic structure pattens of queries from user logs [13].

Experimental results and analysis:

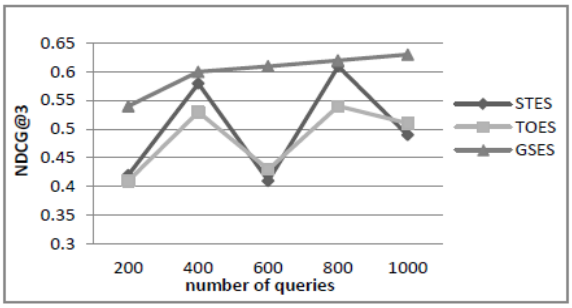

Fig:6. Experimental results and analysis

IX. CONCLUSION

In this paper, we contemplated the pursuit objective move which is one of the imperative conduct attributes of exploratory inquiry and planned another question suggestion technique dependent on the hunt objective move to help exploratory hunt. The strategy utilizes AI to uncover all inquiries amid pursuit objective move forms from internet searcher logs to assemble the inquiry objective move chart and uses irregular walk calculation to acquire question suggestions in the hunt objective move diagram. In the meantime, we demonstrated the adequacy of the suggestion strategy by the relative investigations with different techniques.

A. Future Enhancement

It is not possible to develop a system that makes all the requirements of the user. User requirements keep changing as the system is being used. Some of the future enhancements that can be done to this system are: As the technology emerges, it is possible to upgrade the system and can be adaptable to desired environment. Based on the future security issues, security can be improved using emerging technologies like single sign-on.

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