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DIVERSIFIED QUERY EXPANSION BASED ON USER INTENT FORECASTING

BO ZHANG*, TONGSHU WANG, XIAOXUAN QI, AND GE LOU

Abstract. Diversified query expansion (DQE) is an important branch of search result diversification. This paper finds that expanded queries constructed by traditional DQE methods often cannot effectively meet the current users' intents. Upon analyzing the search log it can be found that a type of ambiguous query, named user-intent-sensitive query, is widely submitted by users, and users' interests in each aspect of this type of query change over time. For traditional DQE methods never forecast the change of users' interests, they typically cannot construct suitable expanded queries for this type of search. In order to address this problem, this paper proposes a method to forecast the change of users' interests in each aspect and designs a DQE method based on the forecasting. A series of experiments show that the proposed method can effectively predict changes in users' interests and select appropriate expansion terms to construct suitable expanded queries based on these changes.

1. Introduction

Queries submitted by users are usually ambiguous [19, 24]. Song et al. find that approximately 16% of queries in logs are ambiguous [21]. The process of DQE generally includes three basic steps: firstly, obtain a series of candidate expansion terms from a data source; secondly, select a series of expansion terms that cover as many query aspects as possible from candidate expansion terms; finally, combine the selected expansion terms with the original query, and use the expanded query to obtain a diversified set of search results. Since the search log contains the real search behaviors of historical users, this paper obtains a series of candidate expansion terms from the historical queries in log.

By observing the log, it can be found that the time of queries submitted by users can aid in forecasting changes in users' interests. Consequently, this paper proposes a user intent forecasting method based on the time dimension, as well as a DQE (Dynamic Query Expansion) method based on user intent forecasting, which is named DQE-UIF. The core of DQE-UIF is to utilize the search behaviors of historical users over time for each query aspect as positive feedback, thereby forecasting the current user's interest in each query aspect. This method not only retrieves documents that the current user is currently interested in but also diversifies the search results simultaneously. DQE-UIF operates in the following steps:

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*Corresponding author.

firstly, it obtains a set of candidate expansion terms from the log and divides these candidate terms into subsets offline according to the query aspects; secondly, DQE-UIF forecasts the current user's interests in each query aspect of the current query and assigns weights to each aspect online; finally, the method extracts a varying number of expansion terms from each subset based on the corresponding weight and appends these expansion terms to the original query.

A series of experiments have been carried out to evaluate the designed method. The experimental results show that DQE-UIF can effectively discover changes in users' interests across various aspects. Secondly, when users' interests change minimally, the search results of expanded queries constructed by DQE-UIF are similar to those obtained using traditional DQE methods. However, when users' interests undergo significant changes, the search results of expanded queries constructed by DQE-UIF show obvious improvements. Specifically, the S-Recall@20 values, α-NDCG@20 values, and NDCG-IA@20 values of the search results are significantly enhanced.

The remainder of this paper is organized as follows. Section two discusses the related work. Section three details the core of DQE-UIF. The experimental setup and evaluation method are introduced in section four. Experimental results are shown in section five. In the last section, the conclusion is given.

2. Related work

Diversified query expansion (DQE) is a direction within search result diversification (SRD), which aims to enhance user satisfaction with SRD. The core idea of DQE is to obtain a set of documents that cover multiple aspects for ambiguous queries, thereby meeting the needs of users with different intents [15]. DQE is not only widely used in traditional query expansion fields [2, 3, 21], but also in abbreviation recognition [13], named entity recognition [5, 6, 19, 23], question-answering systems [7], and domain-specific search [4].

Research [3, 4, 22] never considers which query aspects the current query can be mapped to, but instead selects expansion terms that can cover as many aspects as possible. Bouchoucha et al. use concepts in ConceptNet to judge the relationship between candidate expansion terms and queries, in order to select a final set of expansion terms [3]. Additionally, Bouchoucha et al. analyze the relationship between candidate expansion terms through Wikipedia links and select a group of final expansion terms using the vertex-reinforced random walk algorithm [4]. Vargas et al. selected candidate extension words from a set of documents that were divided into aspects, and then utilized the ts_{xQuAD} algorithm to select a final set of extension words [22]. MacAvaney et al. utilized a Knowledge Base for DQE [13]. Dev et al. obtained candidate extension words from the top-K documents returned by search engines and used a graph-based method to select a set of extension words belonging to a range of potential topics, in order to extend query conditions [6].

Liu et al. believe that if the aspects of the current query are not divided, it may be impossible to cover all aspects of the query, which makes the results of DQE unable to meet the needs of some users [10]. Therefore, Liu et al. design a log-based DQE method. This method firstly divides the aspects of the current query and then selects a series of expansion terms for each aspect. Due to its ability to achieve better aspect coverage, this paper adopts the idea of Liu et al. for DQE.

Nowadays, the core idea of DQE has been applied in numerous domains. Wang et al. [23] and Ning et al. [16] utilize DQE in e-commerce recommendation systems. Mohamed et al. employ DQE in document summarization [14]. Zhu et al. use DQE in query recommendation systems [26].

The above research designs different DQE methods that have obtained very good experimental results. However, in practical applications, the above research has not considered the changes in current users' interests in each aspect over time. At this point, these methods may select extension terms that are no longer of interest to current users, thereby detracting from users' search experience. This is the core problem researched by this paper.

3. Diversified query expansion based on user intent forecasting

3.1. **Aspects Division by Term-Relation Graph.** This paper utilizes the term-relation graph (TRG) [11] to divide the aspects of a query. The TRG can be represented as an N × N matrix E, where N denotes the aspects of terms within the TRG. Each element $e_{m,n}$ represents the relationship between term w_m and w_n.

This paper constructs the TRG based on historical queries in the log. For any given query q, the paper selects a related query collection Q using two types of historical queries. One type consists of queries from the same sessions as q. The other type comprises queries that have the same clicked URL as q. The term collection E for the TRG is compiled from words in historical queries in Q after word segmentation and the removal of stop words. The value of $e_{m,n}$ is computed using Equation (3.1).

$$e_{m,n} = \alpha n_s + \beta n_c. \tag{3.1}$$

Where n_s denotes the number of times term w_m and term w_n belong to the same query, and n_c denotes the number of times query q_m(containing word w_m) and query q_n(containing word w_n) have the same clicked URL.

If w_m and w_n are high related, then $e_{m,n}$ is high; if not, the $e_{m,n}$ is low. At this point, the matrix E can be divided into groups by clustering.

3.2. **Weight Evaluation Method Based on ShiftBand.** For a user-intent-sensitive query q, since the users' interests in different aspects may change, it is necessary to predict the users' interests in each aspect t_i of q prior to query expansion. This section employs the ShiftBand algorithm [2] to predict.

ShiftBand is mainly used to address the problem of the exploitation-exploration trade-off in a multi-round selection process. The procedure of the algorithm is as follows: For a problem with T options, in the i-th round of selection, the algorithm first estimates a coefficient $w_{i,t}$ for each option t, and then estimates the probability $p_i(t)$ that the user will select t based on $w_{i,t}$ in the current round; Subsequently, the user selects an option according to the probability $p_i(t)$ and receives a reward $x_{i,t}$. Finally, the system calculates $w_{i+1,t}$ for the next round based on $w_{i,t}$, $p_i(t)$, and $x_{i,t}$.

In this paper, $p_i(t)$ represents the probability that users submitting the query q in the i-th time period may be interested in topic t. The reward $x_{i,t}$ which indicates the degree of users' actual interest in topic t in the i-th time period, is defined as the number of records $x_{i,t}$ where users actually click on URLs belonging to topic t during that period. At this point, the coefficient $w_{i+1,t}$ for users in the (i+1)-th period can be predicted on $p_i(t)$, $w_{i,t}$, and $x_{i,t}$. Subsequently, the probability $p_{i+1}(t)$ that users will be interested in topic t in the (i+1)-th time period can be predicted.

Based on the above analysis, $p_{i+1}(t)$ for the (i+1)-th period of time can be predicted as follows. Firstly predict $p_1(t)$ using the initial $w_{1,t}$. Then predict $w_{2,t}$ using $p_1(t)$, $w_{1,t}$, and $x_{1,t}$. Subsequently, predict $p_2(t)$ using $w_{2,t}$. This process continues iteratively, allowing for the prediction of $p_{i+1}(t)$ in the (i+1)-th period of time. Note that $p_i(t)$ can be predicted using Equation (3.2).

$$p_i(t) = (1-\epsilon)\frac{w_{i,t}}{\sum_{i=1}^{T} w_{i,t}} + \frac{\epsilon}{T}. \tag{3.2}$$

Where ε is a constant. Then, $w_{i+1,t}$ is predicted using Equations (3.3) to (3.8).

$$w_{i+1,t} = w_{i,t} \cdot exp\left\{\eta_(t,i) \times (\hat{x}_{i,t} + \frac{\epsilon}{T})\right\}, \tag{3.3}$$

$$\hat{x}_{i,t} = x_{i,t}/p_i(t), \tag{3.4}$$

$$\eta_{t,i} = \frac{\alpha S_t + C_{t,i}}{\sum_{t' \in T_q} \alpha S_{t'} + C_{t',i}}, \tag{3.5}$$

$$S_t = \sum_{i=1}^{N} x_{i,t}, \tag{3.6}$$

$$C_{t,i} = \begin{cases} \beta \times \Delta x_{i,t} & \text{if } \Delta x_{i,t} \geq 0, \\ \gamma \times \Delta x_{i,t} & \text{if } \Delta x_{i,t} < 0. \end{cases}, \tag{3.7}$$

$$\Delta x_{i,t} = x_{i,t} - x_{i-1,t}. \tag{3.8}$$

Where $\epsilon \in$(0,1], and α, β, γ are real numbers. Then, the weight of topic t can be computed using Equation (3.9).

$$w_t = \frac{p_i(t)}{\sum_{t' \in T_q} p_i(t')}. \tag{3.9}$$

3.3. **Selecting the Expansion Terms.** A query q can be diversified expanded based on the weight collection W. Assuming that the final number of expansion terms is K, then k_t expansion terms can be selected from the expansion term set SE_t, where k_t=K×w_t. If k_t ¡1, then set k_t =1, i.e. ensure that there is at least one expansion term in the expanded query belonging to topic t.

This paper selects expansion terms using the method of Maximal Marginal Relevance-based Expansion (MMRE) [12]. This method achieves diversification of expansion terms after ensuring the relevance between expansion terms and the original query.

The selection of expansion terms form SE_t is computed using Equations (3.10) and (3.11).

$$e^* = arg_{e \in SE_t \cap e \notin SE^*} max(\lambda \cdot sim(e,q), (1-\lambda) \cdot sim(e,e')), \tag{3.10}$$

$$sim(e,q) = \prod_{e' \in q} sim(e,e'). \tag{3.11}$$

4. Experiment

This section outlines the experiment setup, the baseline method, and the evaluation metrics.

4.1. **Experimental Setup.** The search log used in this paper was collected from 185 student volunteers in the computer department of a university. Each volunteer used a personal computer for their daily searches. The log from each volunteer's computer was automatically collected by a browser plug-in and summarized monthly. The summarized logs span from December 1st, 2007 to November 30th, 2008. The format of the log follows that of major commercial search engines. A record includes the user ID (uid), time, query, the rank of the clicked URL, the order of the click, and the clicked URL itself. In this paper, the log is divided into sessions based on the main research criteria, specifically, the interval between records within a session is not more than 30 minutes [1]. The log comprises 64,346 sessions, 167,228 records, 12,947 unique queries, and 39,490 clicked URLs.

According to Ma et. al. [12], in Algorithm 1, α and β were initially set to 1. However, through a large number of experiments, the parameters were adjusted to $\epsilon = 0.3$, $\alpha = 0.2$, $\beta = 2.5$, and $\gamma = 0.3$.

4.2. **Baseline And Evaluation Metrics.** In order to evaluate the effectiveness of the proposed method, the DQE-UIF method is compared with three other DQE methods: CAE, ts_{xQuAD}, and IAMF+IAD.

The CAE method [13] first establishes a feature vector for each candidate expansion term. Then, it extracts topics from the candidate expansion terms using a single-value threshold algorithm and assigns a weight to each topic. Finally, it selects several expansion terms from each topic based on the topic's weight.

The ts_{xQuAD} method [22] first extracts a series of candidate expansion terms from a selected set of top-ranked documents. Then, it further selects a group of the most diversified expansion terms from these candidates using an improved version of the xQuAD algorithm.

IAMF+IAD [6] is a DQE framework that maps query aspects to a graph model and enhances the diversity of aspect coverage through an Absorbing Random Walk over Mutating Markov Chains.

This paper uses S-recall [25], α-NDCG [5], and NDCG-IA [18] as evaluation metrics to assess the results of query expansion. We employ five teachers to evaluate the expansion terms and search results, with the evaluation results being mapped into levels ranging from 0 (irrelevant) to 5 (high relevance).

In each aspect of the evaluation, we first obtain the search results for the expanded query. Then, we calculate the values of the three aforementioned indicators to evaluate the search results, based on the evaluations of each document in the search results provided by the five teachers.

5. Results and analysis

5.1. Results of Query Expansion When Users' Interests No More Change. This section presents the results of query expansion by each algorithm, assuming that users' interests in each aspect remain unchanged. Figure 1 to Figure 3 show the evaluation results of the query results expanded by four algorithms based on the total log, and Table 1 shows the final evaluation results of the four algorithms. Figure 1 shows the s-recall@20 results of the expanded query generated by four algorithms. Figure 2 shows the α-NDCG@20 distribution of the expanded query. The NDCG-IA@20 results are shown in Figure 3. In this paper, the parameter α in α-NDCG is 0.5.

As shown in Figure 1, the peak of the S-Recall@20 value of ts_{xQuAD} is in the range of (0.4, 0.5), while the peak of the S-Recall@20 value of CAE, IAMF+IAD, and DQE-UIF are in the range of (0.6, 0.7). This is because ts_{xQuAD} only considers maximizing the difference between the expansion terms, but never guarantees that the expansion terms can cover all the aspects. In this case, one or more aspects have no expansion terms in the expanded query, resulting in a relatively low S-Recall@20 for ts_{xQuAD}. This result is consistent with Liu et al. [13]. Due to the absence of expansion terms on some aspects, the α-NDCG@20 and the NDCG-IA@20 of ts_{xQuAD} are lower. As shown in Figure 2 and Figure 3, the peak of the α-NDCG@20 and the NDCG-IA@20 of ts_{xQuAD} are in the range of (0.3, 0.4), while the peak of these three values of CAE, IAMF+IAD, and DQE-UIF are in the range of (0.4, 0.5). Table 1 shows that CAE, IAMF+IAD, and DQE-UIF have higher S-Recall@20, α-NDCG@20, and NDCG-IA@20. This indicates that CAE, IAMF+IAD, and DQE-UIF outperform ts_{xQuAD}. Consequently, the performance of the expanded queries corresponding to these three algorithms can be enhanced by dividing the aspects of ambiguous queries.

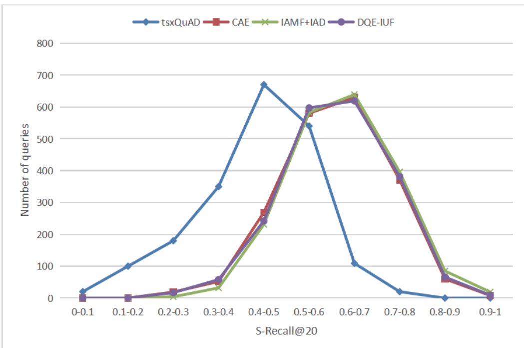

Figure 1. The S-Recall@20 distributions of three methods.

As shown in Figures 1 to 3, the CAE, IAMF+IAD, and DQE-UIF methods have similar performance on S-Recall@20, α-NDCG@20, and NDCG-IA@20. As shown in Table 1, the values of these three methods are approximately the same. This

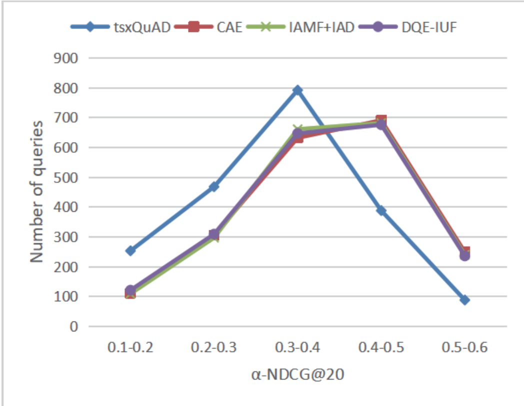

Figure 2. The α-NDCG@20 distributions of three methods.

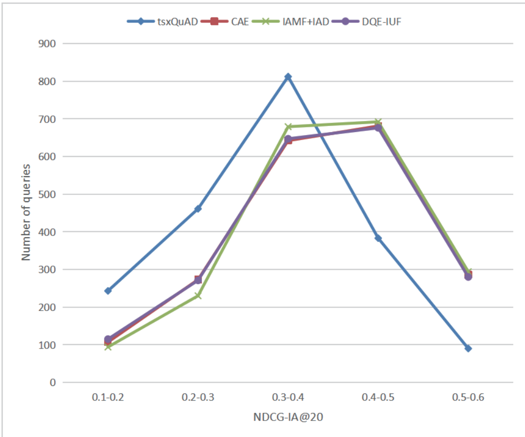

Figure 3. The NDCG-IA@20 distributions of three methods.

Table 1. Results of Different Methods

Method	S-Recall @20	α-NDCG@20	NDCG-IA@20
ts_{xQuAD}	0.441	0.309	0.301
CAE	0.608	0.393	0.399
IAMF+IAD	0.623	0.383	0.393
DQE-UIF	0.611	0.371	0.387

means that DQE-UIF has the same performance as traditional DQE methods when the users' interests in each aspect do not change.

5.2. **Results of Query Expansion When Users' Interests Change Greatly.** This section evaluates query expansion when users' interests change. The results for 534 manually identified user-intent-sensitive queries are shown in Figures 4 to 6 and Table 2.

As shown in Figures 4 to 6, the peak of the S-Recall@20 for DQE-UIF falls within the range of (0.4, 0.6), and the peaks of both the α-NDCG@20 and the NDCG-IA@20 lie within the range of (0.4, 0.5). Compared with CAE, IAMF+IAD, and ts_{xQuAD}, the distribution of these three values for DQE-UIF is closer to the higher part of the figures.

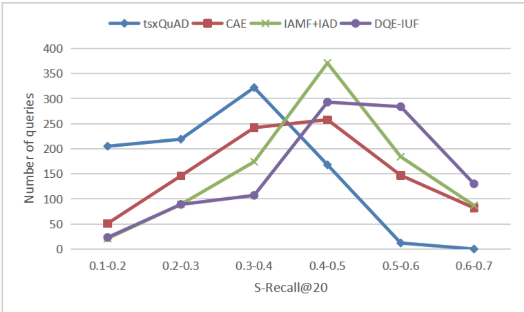

FIGURE 4. The S-Recall@20 distributions of three methods.

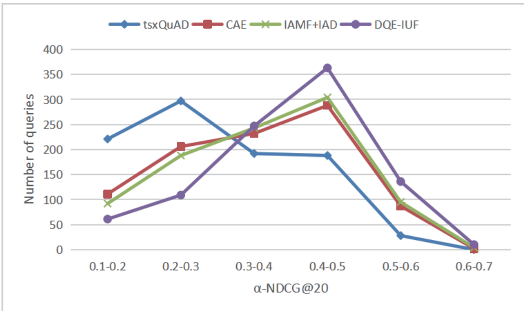

FIGURE 5. The α-NDCG@20 distributions of three methods.

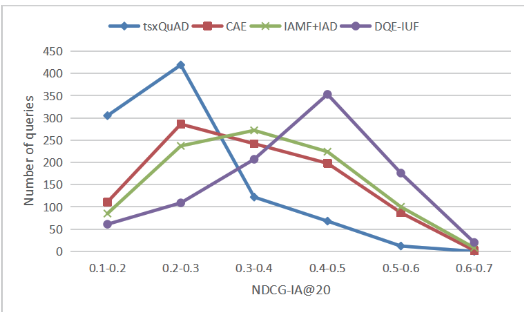

FIGURE 6. The NDCG-IA@20 distributions of three methods.

As shown in Table 2, the S-Recall@20 of DQE-UIF is 7.2% higher than that of CAE, 7.5% higher than that of IAMF+IAD, and 42.9% higher than that of ts_{xQuAD}. Similarly, the α-NDCG@20 of DQE-UIF is 24.6% higher than that of

TABLE 2. Results of Different Methods

Method	S-Recall @20	α-NDCG@20	NDCG-IA@20
ts_{xQuAD}	0.303	0.249	0.297
CAE	0.409	0.336	0.354
IAMF+IAD	0.444	0.364	0.354
DQE-UIF	0.471	0.397	0.408

CAE, 9% higher than that of IAMF+IAD, and 63.9% higher than that of ts_{xQuAD}. The NDCG-IA@20 of DQE-UIF is also 12.1% higher than that of CAE, 15.3% higher than that of IAMF+IAD, and 76.1% higher than that of ts_{xQuAD}.

The results indicate that, because DQE-UIF guarantees the coverage of expansion terms across all aspects, the terms it selects are highly diversified and able to cover as many aspects as possible. Its S-Recall@20 is comparable to those of CAE and IAMF+IAD, but significantly improved compared to ts_{xQuAD}. Since DQE-UIF takes into account the changes in users' interests across each aspect, the expansion terms it selects are more aligned with the distribution of users' interests at any given time, thereby better fulfilling their information needs.

At the same time, the proportion of documents belonging to each aspect among the top-ranked documents is more suited to users' interests in those aspects, resulting in the α-NDCG@20 and the NDCG-IA@20 of DQE-UIF being significantly higher than those of CAE, IAMF+IAD, and ts_{xQuAD}.

6. Conclusions

By observing the logs, this paper finds that there is a type of ambiguous query, named the user-intent-sensitive query, which is widely submitted by users. Traditional DQE methods cannot effectively expand the user-intent-sensitive query when users' interests in one or more aspects change. To address this problem, this paper introduces the time dimension to forecast changes in users' interests across each aspect of the current query, and proposes a diversified query expansion method called DQE-UIF based on the results of this forecasting. A series of experiments demonstrate that the DQE-UIF method proposed in this paper can promptly capture changes in users' interests across each aspect, and then selects an appropriate number of expansion terms for each aspect to form the expanded query. As a result, the expanded query generated by DQE-UIF better meets the current users' interests. Compared with traditional DQE methods, such as CAE, IAMF+IAD, and ts_{xQuAD}, the α-NDCG@20 value and NDCG-IA@20 value of DQE-UIF are significantly improved.

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B. Zhang
School of Intelligent Science and Information Engineering, Shenyang University, Shenyang, China
E-mail address: programboy007@163.com

T. Wang
School of Intelligent Science and Information Engineering, Shenyang University, Shenyang, China
E-mail address: 3030148144@qq.com

X. Qi
School of Intelligent Science and Information Engineering, Shenyang University, Shenyang, China
E-mail address: qi_xx@aliyun.com

G. Lou
PokTai Technology Shenyang Co., Ltd, Shenyang, China
E-mail address: louge_poktai@163.com