C-DLSI: An Extended LSI Tailored for Federated Text Retrieval

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Abstract—As the web expands in data volume and in geographical distribution, centralized search methods become inefficient, leading to increasing interest in cooperative information retrieval, e.g., federated text retrieval (FTR). Different from existing centralized information retrieval (IR) methods, in which search is done on a logically centralized document collection, FTR is composed of a number of peers, each of which is a complete search engine by itself. To process a query, FTR requires firstly the identification of promising peers that host the relevant documents and secondly the retrieval of the most relevant documents from the selected peers. Most of the existing methods only apply traditional IR techniques that treat each text collection as a single large document and utilize term matching to rank the collections. In this paper, we formalize the problem and identify the properties of FTR, and analyze the feasibility of extending LSI with clustering to adapt to FTR, based on which a novel approach called Cluster-based Distributed Latent Semantic Indexing (C-DLSI) is proposed. C-DLSI distinguishes the topics of a peer with clustering, captures the local LSI spaces within the clusters, and consider the relations among these LSI spaces, thus providing more precise characterization of the peer. Accordingly, novel descriptors of the peers and a compatible local text retrieval are proposed. The experimental results show that C-DLSI outperforms existing methods.

I. INTRODUCTION

Due to the highly dynamic nature of the World Wide Web, traditional search engines (SEs) must face great challenges on scalability and adaptability. Because of the limited resources available to a search engine, it is hard to catch up with the fast expansion of the Web and the frequent updates of its contents. Consequently, the overall coverage of the search engines with respect to the size of the entire web deceases with time. We need a scalable and highly efficient search and index mechanism to make the data on the web in a timely manner accessible.

To overcome these difficulties, in the past decade, various information retrieval (IR) methods based on parallel and distributed computing have been proposed. Among these methods, parallel information retrieval [14] that maintains a single index and employs a server cluster to balance the load has been well studied and successfully applied in real-world search engines such as Google. However, it is not scalable with respect to the size and dynamics of the Web. Furthermore, it cannot handle the hidden deep web because of privacy issues. To alleviate these problems, federated information retrieval [28] and meta-search [22] were proposed. They send a query simultaneously to multiple search engines, collect the results from each search engine after the query has been evaluated separately, and last merge the results together (i.e., re-ranking).

In this way, there is no need to access directly to the pages or the index at each search engine. FIR makes it possible to take advantage of the power of different search engines and provide large coverage of the Web. Since FIR facilitates cooperation among search engines, it can be more efficient and effective than meta-search. For this reason, FIR has attracted much attention in recent years.

As a promising solution to the scalability and adaptability problems, FIR aims to support search on a large amount of data in a distributed and self-organizing manner. In the FIR framework, each search peer indexes and maintains its own document collection, thus avoiding management problems associated with large data centers. A broker is introduced to maintain a directory of the peers together with summarization information, named descriptors, about them. For query processing, the broker will select peers that have high potential to return relevant documents for the query according to the peer descriptors. Note that the broker does not have to know the peers’ indexes or original document sets. In this paper, we only consider textual documents and content relevance in retrieval, so we name it federated text retrieval (FTR).

In conventional centralized IR methods, query processing only focuses on the problem of finding relevant documents using a single index. On the contrary, FTR requires a three-phase query processing procedure. First, it identifies promising peers which may return the most relevant documents. Then it submits the query to the selected search engines, each of which retrieves the results from its collection. Finally, it merges the results together and returns them to the user. Peer selection plays a key role in FTR, which is also the major concern of this paper. With peer selection, we can make query evaluation more efficient and, at the same time, save a lot of computing resources (e.g., power, communication bandwidth, CPU time, etc.). A number of peer selection approaches [5], [10] have been proposed, but they are mostly based on the word histogram of the peers and traditional term matching techniques.

Obviously, the content structure in a collection is signifi-
This paper. Section 5. The last section summarizes the results obtained in experimental setup and corresponding results are showed in problem and present our approach C-DLSI in details. The introduced in Section 3. In Section 4, we formalize the Latent Semantic Indexing (LSI) and K-means Clustering are some bases of our method, including the framework of FTR, among the clusters. In this paper, we propose a novel approach called Cluster-based Distributed Latent Semantic Indexing (C-DLSI) based on a formal analysis of the problem. In particular, C-DLSI, by applying clustering to distinguish the topics of a peer, extends the traditional LSI scheme and captures delicate semantic features of the peer, thus providing more precise characterization of the peer. Moreover, our method is quite scalable and cost-efficient for the updates.

We detail our main contributions as follows:

1) An LSI-based framework (C-DLSI) for text retrieval in distributed environments was proposed. It encompasses directory maintenance and query processing.
2) Identification of the properties of FTR and the feasibility analysis of extending LSI with clustering to improve the quality of peer representation. Specifically, the relations among the clusters are considered in C-DLSI to adapt to the properties of FTR. Our method is efficient and adapts to frequent collection updates since only the clusters affected by the updates need to be reindexed.
3) Based on the analysis of C-DLSI, novel descriptors of the peers are proposed and a complete federated query processing strategy in FTR is developed.
4) The extensive performance evaluation of C-DLSI on a TREC dataset. Impacts of different parameter selections are fully discussed.

The rest of the paper is organized as follows. In Section 2, we review the related work on FIR and peer selection. Some bases of our method, including the framework of FTR, Latent Semantic Indexing (LSI) and K-means Clustering are introduced in Section 3. In Section 4, we formalize the problem and present our approach C-DLSI in details. The experimental setup and corresponding results are showed in Section 5. The last section summarizes the results obtained in this paper.

II. RELATED WORK

Peer selection is a critical problem in FTR and distributed information retrieval systems in general. It has been studied for more than a decade. Many methods have been proposed to address this issue. gGloss (generalized Glossary-Of-Servers Server) [10], [11] is a well-known method. It keeps statistics (document frequencies and total weights) about the servers to estimate which servers are potentially most useful for a given query. In particular, gGloss(0), a special form of gGloss, which aggregates all similarity values between the documents and the query, was shown to be the best and has been widely employed for comparison [6], [27], [32]. In this paper, we also use it as a baseline.

The Collection Retrieval Inference Network (CORI) [5], [25] is another important work. It drew analogy between collection ranking and document ranking and applied some form of $TF \times IDF$ ranking strategy to rank the collections. Specifically, it replaces TF with DF (document frequency), and IDF with ICF (inverse collection frequency), the inverse of the proportion of the collections carrying at least one document which contains some query terms. Moreover, Yuwono and Lee [36] proposed the cue-validity variance (CVV) method for collection selection. CVV measures the skewness of the distribution of a term across the collections and estimates the usefulness of the term for distinguishing a collection from another. Then terms with larger variances will be given larger weights in index collection ranking. An evaluation of a number of collection selection methods in a Web environment was given in [6]. None of these methods consider the topic space of the peers and utilize semantic information beyond simple term matching to make a selection.

Latent Semantic Indexing (LSI) [7] was originally proposed to take advantage of implicit high-order structure in the association between terms with documents, namely, semantic structure, to improve the retrieval of relevant documents. Much efforts have been made to improve its performance [19], [15], [13], or broaden its applications [24]. An earlier work which tried to utilize LSI to improve the peer selection of FTR is the latent semantic database selection (LSDS) [32]. It simply applied LSI to preprocess the document collections, and conventional selection methods (e.g., CORI) on the “cleaned” term/document matrices for ranking the collections. However, this method did not capture the key properties of FTR and, moreover, inherited the disadvantages of the conventional methods, e.g., ignoring the topic space of the peers and the drawbacks inherited from CORI.

To overcome the deficiencies of traditional methods, cluster-based approaches were proposed to identify the topic space of the peers. Document clustering was applied to organize collections around topics and then language modeling was used to represent the topics [35]. This method allows the right topics to be effectively identified for a given query. However, this method cannot distinguish the documents within a topic. Shen and Lee [27] proposed another cluster-based method IS-cluster which utilized cluster descriptors to rank the servers for meta-search engine. We also use this method as a candidate for comparison in our experiments. Term correlation was introduced to further improve cluster-based methods [38]. However, it did not consider the compatibility issue in FTR, which means that peer selection should adapt to the local document ranking functions. Further, it is very difficult to determine the parameters in the method. In this paper, we extend LSI with the clustering method to especially adapt to FTR and achieve better retrieval performances.

Recently, uncooperative federated search systems have been
studied. In this case, collections do not disclose their index statistics to the broker. The broker has to sample documents from each collection and uses them for collection selection. ReDDE \cite{29} estimates the number of relevant documents in collections and uses it to improve collection selection. Estimation of the needed information for collection selection from an uncooperative peer was addressed in \cite{21,23}. Introduced a decision theoretic framework (DTF) for collection selection, which tries to minimize the overall costs of federated search including money, time, and retrieval quality. Similarly, \cite{30} proposed a unified utility maximization framework (UUM) for resource selection, which evaluates queries on sampled index. Furthermore, an enhanced model called RUM \cite{31} was proposed by considering the search effectiveness of collections. In general, they do not consider the topic space of the peers either and ignore the semantics. Thus, C-DLSI can also be embedded into these methods with slightly change (e.g., applied on the sampling documents) to adapt to this new scenario.

III. PRELIMINARIES

In this section, we introduce some preliminaries which act as the bases of our C-DLSI method. In particular, we first present the general FTR framework in Section 3.1. Then we describe two important techniques Latent Semantic Indexing (LSI) and document clustering in Section 3.2 and Section 3.3, respectively.

A. FTR Framework

As a federated information retrieval scheme, FTR provides a loose cooperation among search peers in which each peer maintains its own local index and a central broker is employed to coordinate the cooperative text retrieval. Specifically, each peer has a complete search engine in itself. That is, it has its own crawler, index and search component for information gathering, organizing and retrieving, respectively. Besides, the peers share a common descriptor publishing scheme to disclose to the broker summaries of information in their repositories. On the other side, the broker of the FTR system take charge of the query processing by maintaining a centralized directory, which holds the descriptors of the peers’ local indexes.

In FTR, two basic functions are supported: directory maintenance (or peer descriptor publishing) and query processing. Figure 1 shows the whole framework of FTR. First, each peer summarizes the descriptor for its local index and publishes it to the directory in the central broker. These descriptors are used by the broker to select suitable peers in query processing. This process is known as the peer representation problem \cite{3}. Usually, a descriptor contains connection information together with statistics for each term in the peer or a limited number of sampled documents. In this paper, we will provide a novel solution to peer representation in Section 4.3.

When a query arrives at the broker, the broker selects the most promising peers which may return the most relevant documents based on the descriptors. This is the peer selection problem \cite{5}. Then the query is forwarded to the selected peers. Based on the local index, each peer evaluates the query and returns the results to the broker. Once receiving the results, the broker will employ a reranking method to properly merge the results together and present them to the user. It is called the result merging problem. We will consider these issues of the federated query processing in Section 4.4.

B. Latent Semantic Indexing

Latent Semantic Indexing (LSI) proposed by Deerwester et al. aims at taking advantage of the semantic structure of a document collection to improve retrieval performance. Its objective is to overcome the fundamental deficiencies of conventional keyword-based information retrieval techniques. The problem stems from the fact that users are interested in documents which share the same conceptual content with the queries, but traditional IR techniques only perform keyword matching between queries and documents and thus cannot deal with synonymy and polysemous problems. To bridge the gap, LSI applies singular value decomposition (SVD) on a term-document matrix to statistically extract the implicit high-order structure in the association of terms with documents, which can be used to find the semantic representations of documents.

LSI is an extension of the vector space model, which approximates the term-document matrix by the truncated SVD of the matrix. Given an $m \times n$ term-document matrix $A$, the SVD of $A$ is

$$A = U \Sigma V^T,$$  \hspace{1cm} (1)

where $U$ and $V$ have orthonormal columns, $\Sigma$ is a diagonal matrix having the singular values of $A$ in decreasing order (denoted as $\sigma_1, \sigma_2, \ldots, \sigma_{\text{rank}(A)}$) along its diagonal, and $T$ denotes the transpose of a vector or a matrix. LSI decompose $A$ to a lower dimensional vector space $k$ by retaining only the largest $k$ singular values, where $1 \leq k < \text{rank}(A)$. Specifically,

$$A_k = U_k \Sigma_k V_k^T,$$ \hspace{1cm} (2)

where $U_k$ and $V_k$ consist of the first $k$ columns of $U$ and $V$ respectively, and $\Sigma_k$ is the $k \times k$ diagonal matrix containing the largest $k$ singular values of $A$. Because the number of factors $k$ can be much smaller than the number of unique terms used to construct this space, terms will not be independent and the
terms with similar meaning will be located near one another in the LSI space. The relevance score of a document vector \( d \) with a query vector \( q \) is measured by the cosine or dot product between the document vector \( d_k \) in LSI space and \( q \). Without loss of generality, we assume that all vectors are normalized. Then the relevance score can be described as,

\[
s(d, q) = d_k^T q.
\]

In this paper, we apply the distributed latent semantic indexing to peer selection and document ranking.

C. Document Clustering

Since a peer contains a large number of documents, it potentially covers multiple topics compared to that of a single document. Thus, a word histogram created for the entire peer cannot provide a precise description of the peer, making it inadequate to apply a document ranking approach to peer ranking. A proper peer selection should consider the topics covered in the peers. In our framework, we utilize a clustering technique to group the documents of a peer and treat each cluster as an approximate topic. Then the peer is evaluated based on the clusters’ relevance scores with respect to a given query.

Although the clustering process is an offline process in the framework, we still need an efficient clustering method that can handle a large number of documents and adapt to updates on the peers. In this paper, we adopt the widely used k-means clustering algorithm \( [14] \) to deal with these problems. It uses an iterative procedure to find \( K \) partitions of objects, which minimize the total intra-cluster variance (or the squared error function). Specifically, it starts with \( K \) randomly selected objects to serve as the centroids and divides the objects according to the distances from them. Then it generates \( K \) new centroids based on the current partitions and starts another round of division until a stable state is reached. Empirically, the k-means algorithm can converge quickly and is considered to be very efficient. For document space, k-means is to maximize the following measure:

\[
I = \sum_{i=1}^{K} n_i \mu_i^T \mu_i
\]

where \( n_i \) denotes the document number of the \( i \)th cluster, and \( \mu_i \) the centroid of the \( i \)th cluster.

It is proven that the solution to the k-means clustering method coincides with the principal points solution \( [2] \), which means it is a point-representation scheme where the best \( K \) representative points (i.e. topics) are obtained. On the contrary, SVD provides a component-representation of the document space and ensures the best representation of the information content in a reduced dimensional vector space. We will show that extending LSI with clustering can especially adapt to FTR.

IV. FTR with C-DLSI

In this section, we present the details about our cluster-based distributed latent semantic indexing (C-DLSI) method for FTR. By identifying the special properties of FTR, we extend LSI accordingly to treat the peer selection issue, which overcomes the deficiencies of the conventional approaches. In Section 4.1, we first formulate the peer selection problem in FTR, analyze the properties, and identify the deficiencies of the traditional approaches. Then we propose the C-DLSI method especially tailored for FTR in Section 4.2. Based on C-DLSI, the corresponding descriptors and a federated query processing in FTR are presented in Section 4.3 and Section 4.4, respectively. Finally in Section 4.5, we describe an update scheme for a peer in a highly dynamic environment.

A. Properties of Peer Selection in FTR

In FTR, if the distribution of relevant documents across the results returned by the peers were known, the peers could be ranked by the number of relevant documents they return, which is known as relevance-based ranking (RBR) \( [4] \). Consider a set of peers \( M = \{ p_i \} \). To simplify the explanation, we assume that each peer is required to return the top \( N \) results, i.e., \( \theta_i = \{ d_{ij} \} \) \( (1 \leq j \leq N) \) with decreasing relevance score for peer \( p_i \). Let \( r(d, q) \) denote the probability of relevance for document \( d \) given query \( q \). The ranking value \( r(p_i, q) \) for peer \( p_i \) can be represented as,

\[
r(p_i, q) = \sum_{j=1}^{N} r(d_{ij}, q) \tag{5}
\]

Assume that the global weight of a term in each document is given. There are two major issues here. One is how to determine a proper relevance value \( s(d_{ij}, q) \) which can approximate \( r(d_{ij}, q) \) well. The other is how to summarize the descriptors of the peers based on which the ranking value \( r(p_i, q) \) can be properly estimated.

A simple solution is to estimate the relevance score \( s(d_{ij}, q) \) by computing the inner products between \( d_{ij} \) and \( q \) which is called gGloss(0) \( [10] \) and can be described as,

\[
s(d_{ij}, q) = d_{ij}^T q \tag{6}
\]

By only maintaining the document number \( n_i \) and the centroid \( \mu_i \) of the peer \( p_i \), the broker can estimate the ranking value of peer \( p_i \) as,

\[
r(p_i, q) = n_i \mu_i^T q \tag{7}
\]

which is equal to \( \sum_{i=1}^{n_i} s(d_{ij}, q) \). To solve the problem of various \textit{idf} values of a term among peers, CORI \( [5] \), on the other hand, estimates the ranking value by using the term frequency of each query term in each peer. A further improvement of CORI is to combine it with LSI \( [22] \). Since these methods do not consider the topic space of the peers, the effect of polysemy, i.e., some terms common to two conceptually independent topics, is ignored. Different from document ranking, peer ranking is suffered from the polysemy issue more seriously, because the accumulation of small semantic deviations of the documents may lead to big error in peer ranking. For example, consider a collection of two documents. One is related to "apple, fruit" while the other is related to "computation, math". If we ignore polysemy, we may draw the conclusion that the set is related to "apple computer", even
though the individual relevance scores of the documents with the query "apple computer" are not high.

A direct way to solve the polysemy issue is to use clustering to identify the topics in a peer. Consider a conceptually homogenous cluster. If it is regarded to be relevant to a query, say, "apple, computer, product", then a document in it which does not contain any query terms, e.g., talking about "MacBook, OS", is still likely to be relevant to the query. Therefore, we should also consider the synonyms in a cluster. Unfortunately, to the best of our knowledge, none of the existing methods can adapt well to this situation. For example, if we directly apply LSI on the whole collection and then cluster the documents, then the polysemy cannot be effectively identified by LSI. [27] tried to solve this problem by representing a document with the descriptor of its cluster. Specifically, the weight $\overline{w}_t$ of a term $t$ in the descriptor of a cluster $c_i$ is computed by,

$$\overline{w}_t = \sum_{d_{ij} \in c_i} w(d_{ij}, t) / n_{i,t}$$

where $w(d_{ij}, t)$ denotes the weight of term $t$ in document $d_{ij}$ and $n_{i,t}$ the number of the documents in $c_i$ which contain term $t$. We can see that, to handle synonyms, the weight of a term in the descriptor is estimated only according to the documents which contain them. Then similar formulas as (6) and (7) are utilized to compute the ranking value of the peers. Similarly, [55] employs language model to determine the relevant cluster and all of the documents in a relevant cluster are regarded to be relevant. However, these methods are restricted by two major drawbacks. First, they rely heavily on the quality of clustering and do not consider the relations among clusters. Second, since they assume that all the documents in a cluster is equally relevant, it may exaggerate the relevance score of weakly relevant or irrelevant document and is difficult to decide a proper ranking list of the documents, which is known as a compatibility issue. To overcome these limitations and adapt to the properties of FTR, we extend LSI with clustering which considers the relations among clusters and captures more accurate descriptions of the peers.

B. Cluster-based Distributed LSI (C-DLSI)

In our method, the collection of a peer is partitioned into a number of clusters $\{c_i\}$ (using k-means clustering). Then, LSI is employed to derive the semantic structure within each cluster, i.e., LSI space $C'_i = U_i \Sigma_i V'_i^T$ for cluster $c_i$ with term-document matrix $C_i = U_i \Sigma_i V_i^T$. To make the LSI spaces among clusters comparable, we restrict $C'_i$ with singular values larger than a threshold $\varepsilon$. Let $\sigma_{i,j}$ denote the $j$th singular value in $\Sigma_i$ and a number $k$ satisfy,

$$\sigma_{i,j} \geq \varepsilon, \, 1 < j \leq k$$

$$\sigma_{i,j} < \varepsilon, \, k < j \leq rank(C_i)$$

Then, the LSI space of $C_i$ is redefined as,

$$C'_i = (C_i)_\varepsilon = (U_i)_k (\Sigma_i)_k (V_i)_k^T$$

Consider a diagonal block matrix $A$ for a peer with the form,

$$A = \begin{pmatrix} C_1 & C_2 & \ldots & C_K \end{pmatrix}$$

where $C_i$ represents a conceptually independent topic, e.g., cluster $c_i$. It is easy to prove the following relation [20],

$$A_{\varepsilon} = \begin{pmatrix} (C_1)_\varepsilon \\ \vdots \\ (C_K)_\varepsilon \end{pmatrix}$$

It means if a collection is perfectly divided into a number of conceptually independent topics and no polysemy exists, the LSI space of a peer built in our method is equal to the traditional LSI which is directly applied on the whole collection. Obviously, the LSI spaces of the clusters can distinguish and capture the semantics of the documents more precisely than the existing methods. In the rest of this subsection, this idea will be further improved.

Each peer maintains the semantic structures of its clusters for descriptor generation and federated query processing. Thus, we call our method cluster-based distributed LSI (C-DLSI). Generally, the clusters of a peer may have some relations from each other because of several reasons, e.g., some topics are not conceptually independent in nature or the clustering is not perfect enough and some documents belonging to one topic are separated. In C-DLSI, a semantic similarity measure between any two clusters (named paired similarity) is introduced. This measure is estimated based on the similarity of the LSI vector spaces and consequently, a network of clusters is formed from words shared by each pair of clusters. With the similarity network of clusters, C-DLSI can further exploit the synonyms without loss of the polysemy information. Therefore, it can especially adapt to FTR.

Similar to [7], we define two levels of the paired similarity. Consider two clusters $c_i$ and $c_j$ ($i \neq j$). Let $T_i$ denote the term set for a cluster $c_i$ and $T_{ij}$ the common term set for $c_i$ and $c_j$. The first level of paired similarity $S1$ only captures the frequency of occurrence of common terms. If $c_i$ and $c_j$ have common terms, we say there is a direct link between them. Define the proximity of $c_i$ and $c_j$ to be the minimal number of the intermediate clusters which link $c_i$ and $c_j$. Let $l$ denote the proximity between $c_i$ and $c_j$, then $S1(c_i, c_j)$ is defined as (we only consider the case of $l \leq 1$),

$$S1(c_i, c_j) = (1/S_{ij}^1 + l)^{-1}$$

where,

$$S_{ij}^0 = \frac{|T_{ij}|^2}{|T_i||T_j|}$$

$$S_{ij}^1 = \max_m \frac{|T_{im}|^2|T_{mj}|^2}{|T_i||T_m|^2|T_j|}$$

Moreover, a further level of the paired similarity captures the semantics of the common terms, denoted as $S2$. Let $B_{ij} = ...$
where \( c \) are employed to extend the LSI space built in a cluster. Consider, then the relevant documents in cluster 3 will be query “computer”, if only the LSI space within a cluster is some conceptually relevant terms such as “MacBook” and “apple” can be identified. Obviously, the polysemy of term “apple” can be identified based on these definitions, the paired similarity between cluster \( c_i \) is computed as the sum of the relevance scores of \( c_i \) to all of the terms in \( q \), which can be represented as,

\[
s(c_i, q) = \sum_{t \in T_q} s(c_i, t)
\]

(16)

The relevance score of cluster \( c_i \) to a term \( t \), i.e., \( s(c_i, t) \), can be estimated in two cases.

1) If \( t \in T_i \), we have,

\[
s(c_i, t) = n_i \mu_{i,t} q_t
\]

(17)

where \( n_i \) is the number of documents in \( c_i \) and \( \mu_{i,t} \) is the weight of \( t \) in the centroid \( \mu_i \) of the LSI space of \( c_i \).

2) If \( t \notin T_i \), the relevance score cannot be derived directly by using the LSI space of \( c_i \). Then we can rely on its relevant clusters \( L_i \) to estimate the relevance score. Let \( c_{im} \) be the first cluster of \( L_i \) which satisfies \( t \in T_{im} \). The projection of \( t \) into the LSI space of \( c_{im} \) can be presented as,

\[
t' = B'_{im,t} q_t
\]

(18)

where \( B'_{im,t} \) denotes the column of \( B'_{im} \) which corresponds to term \( t \). Therefore, the relevance score of \( c_i \) to term \( t \) can be approximated as,

\[
s(c_i, t) = n_i \mu_{i,t} t' = n_i \mu_{i,t} B'_{im,t} q_t
\]

(19)

With the relevance scores \( \{s(c_i, q)\} \) of the clusters \( \{c_i\} \) to the query \( q \), we can estimate the ranking value of a peer \( p \). Let \( c_1, \ldots, c_K \) be the clusters of \( p \) with decreasing relevance scores. Then the ranking value is estimated by considering the most \( h \) relevant clusters, which can be represented as,

\[
r(p, q) = \sum_{i=1}^{h} s(c_i, q)
\]

(20)

Moreover, C-DLSI is efficient and scalable, since the size of a cluster is substantially smaller than that of the entire collection. With regard to document updates, it only requires reindexing of the affected clusters. Thus, it is suitable for highly dynamic environment in which documents are frequently updated.

C. Descriptors of Peers

A peer will publish a descriptor of its content to the broker for peer selection. In C-DLSI, since a collection has been clustered, the descriptor of a peer consists of a set of cluster descriptors. According to Formulas (16) \( \sim \) (20), we need at least the document number \( n_i \), the centroid of the LSI space \( \mu_i \), and the eigen matrix \( U_i^T \) to describe a cluster \( c_i \). However, \( U_i^T \) is usually quite large and may cause heavy communications between the broker and the peers. To overcome this difficulty, we rewrite Formula (19) as follows,

\[
s(c_i, t) = n_i \mu_{i,t} B'_{im,t} q_t = n_i (B'_{im,t} \mu_i)^T q_t
\]

(21)

It means we only need a value \( B'_{im,t} \mu_i \) instead of the vector \( B'_{im,t} \) to estimate the relevance score. For any term \( t \), a list of vectors \( \rho_t = \{U_1^T, U_2^T \mu_i, \ldots, U_K^T \mu_i\} \), which correspond to the order of the relevant clusters \( L_i = \{c_1, \ldots, c_n\} \),
are guaranteed to find the value $B_{i,m}^T \mu_t$. Therefore, the transmission of the matrix $U_i^T$ can be saved. Based on this, we define the descriptor $D_i$ for cluster $c_i$ in C-DLSI to contain the following aggregate information:

1) The total number of documents in the cluster, $n_i$.
2) The centroid of LSI space in the cluster, $\mu_i$.
3) A list of vectors $\rho_i = \{U_i^T \mu_i, \ldots, U_i^T \mu_i \}$, which correspond to the order of the relevant clusters $L_i = \{c_i, \ldots, c_i\}$.

That is,

$$D_{c_i} = \{N_i, \mu_i, \rho_i\} \quad (22)$$

Then we define the descriptor $D_p$ for peer $p$ as,

$$D_p = \{D_{c_i} | c_i \in p\} \quad (23)$$

which represents the peer with more fine-grained descriptions of its clusters. Since the number of clusters $K$ is extremely small, publishing this descriptor causes little overhead in C-DLSI.

Note that we assume in this paper that there is little or no overlap among the peers. This is a reasonable assumption in most cases. Since each peer is supported to cover a different part of the web, it corresponds to a distinct database. When this assumption is violated, we can add more aggregate information into cluster descriptors as proposed in [1].

D. Federated Query Processing

As described in Section 3, federated query processing in FTR contains three steps, namely peer selection, local text retrieval, and result merging. In this subsection, we will discuss these three issues in C-DLSI.

As discussed in Section 4.2, the broker compute the ranking values for all the peers according to Formula (20) based on the descriptors. In particular, when computing the relevance score of a cluster $c_i$ to a term $t$ of the query $q$ with $t \notin T_i$, the broker will scan the list $\rho_i$ and find the first relevant cluster $c_{i,m}$ which contains $t$. Then the relevance score $s(c_i, t)$ is computed by,

$$s(c_i, t) = n_i \rho_{i,m}^t q_t \quad (24)$$

where $\rho_{i,m}^t$ denotes the weight of $t$ in the $m^{th}$ vector of $\rho_i$. Otherwise, the relevance score $s(c_i, t)$ can be directly computed according to Formula (17). The broker will choose the peers with largest ranking values and forward the query $q$, together with the IDs of the $h$ most relevant clusters, to each of them. Then it enters the phase of local retrieval.

Local retrieval is performed by peers to retrieve relevant documents from the collections. C-DLSI only considers the LSI spaces of the $h$ most relevant clusters specified by the broker. The relevance score of a document $d_j$ to query $q$ is evaluated based on its LSI vector $d_j'$ in the corresponding cluster $c_i$. Similarly, we have,

$$s(d_j, q) = \sum_{t \in T_q} s(d_j, t) \quad (25)$$

If $t \in T_i$, then the relevance score of the document $d_j$ to term $t$ can be computed by,

$$s(d_j, t) = d_j'^t \mu_t \quad (26)$$

where $d_j'^t$ denotes the weight of $t$ in $d_j'$. Otherwise, the first cluster in $L_i$ which contains term $t$ will be found, denoted as $c_{i,m}$ and the relevance score is estimated as,

$$s(d_j, t) = d_j'^T B_{i,m}^T q_t \quad (27)$$

Thus, the evaluated documents can be sorted according to their relevance scores, and only the top-ranked documents will be returned as the results to the broker.

Result merging in FTR tries to provide a uniform ranked list of the documents returned from multiple peers. Assume that each peer has the global weights for all of the terms in the documents and applies the same ranking function. Then the relevance score of a document estimated by the peer is also valid as a global score among all peers. Thus, we can simply merge the documents according to their relevance scores returned by the corresponding peers in C-DLSI.

Another factor considered in our framework is the compatibility between peer selection and local text retrieval. Since the goal of FTR is to retrieve valuable peers that can return most relevant documents, this process is also impacted by local text retrieval schemes. Thus it requires the peer selection and local text retrieval to be compatible and consistent, which is called the compatibility issue. In C-DLSI, we try to guarantee this property in peer selection method and local text retrieval. Previous research has shown that LSI can help improve document retrieval in a single collection. However, most conventional methods for peer ranking are more likely to select the peers with the largest number of weighted keywords, which does not conform to the basic principle of LSI. Moreover, though several peer selection methods consider the semantic structures of the collections, they ignore the compatibility issue or it is hard to find a proper local text retrieval method to adapt to their peer ranking scheme.

E. Collection Update

Although our C-DLSI method employs LSI in a distributed way and only requires applying SVD in a relatively small scale (i.e., on clusters only), collection update could still be costly for extremely large and dynamic collections. In our framework, we utilize a lazy scheme to handle this problem. In particular, each peer keeps all of the semantic transformation matrices $\{U_i^T\}$ of its own clusters (refer to Section 4.2). When an update occurs, e.g., due to textual update or newly crawled documents, it will first assign the updated documents to the most related clusters, e.g., cluster $c_i$, and then directly use $U_i^T$ to evaluate the semantic vector $d_j'$ according to the following formula:

$$d_j' = U_i^T U_i'^T d_j \quad (28)$$

where $d_j'$ is the updated document vector. It can be easily proven that this form is consistent with the original form of Formula (2). If the amount of updates exceeds a threshold for a
cluster, the corresponding peer will rebuild its LSI by applying SVD on the cluster again. This update handling scheme is also tested and analyzed in the experiments.

V. EXPERIMENTS

To evaluate the C-DLSI method, we build a simulation platform with one broker and 50 peers. The documents come from the TREC collection Volume 4 and Volume 5, which consist of over 500,000 documents with about 2.1GB in total size. In this section, we will first present the setup of the experiments, and then show the results from the C-DLSI evaluation.

A. Experimental Setup

In our experimental platform, we use the documents of the TREC collection Volume 4 and Volume 5. The queries are extracted from TREC-6 ad hoc topics (topics 301 – 350). To simulate short Web queries, we use the terms appearing in the Title field of the topic description as the keywords. In the following experiments, we will also discuss the effect of query length on C-DLSI. Moreover, the standard relevance judgments provided by NIST are used to evaluate the retrieval effectiveness. Since only a portion of the documents are indexed, to make the evaluation more reasonable. In particular, the selected documents are uniformly distributed to 50 indexing collections, which is considered the hardest scenario compared to a skewed distribution [27]. Table 1 gives a summary of the data set used in the experiments. Figure 4 and Figure 5 show the statistics of the indexed documents for each query. We can see that the number of relevant documents for each query is relatively small and it is not easy to identify them for most queries.

We use the LogEntropy weighting scheme [8] to compute the weight vector of each document, which is defined as

\[ w_{ij} = \left[ \log_2 \left( 1 + tf(i, j) \right) \right] \cdot \left[ 1 + \sum_j p_{ij} \log_2 p_{ij} \log_2 n \right] \]

where \( tf(i, j) \) is the frequency of term \( i \) in document \( j \), \( n \) is the total number of documents in the collection, and \( p_{ij} = tf(i, j)/ \sum_j tf(i, j) \). The parameters and their settings used in the experiments are shown in Table 2. Generally, the effectiveness of a FTR system is not evaluated by the precision at recall points. Since only a subset of the peers is selected, it is usually impossible to retrieve all of the relevant documents. As in other research works [29], we use two metrics to evaluate the quality of the merged results. One is the top-N precision (P@N), which can be defined as follows.

\[ P(q, N) = \frac{|R(N)|}{N} \]

where \( R(N) \) stands for the set of relevant documents in the top \( N \) results. As a complement, we also use another metric named top-N average precision (AP@N) to evaluate the distribution of the relevant documents in the top-N results. AP@N is defined as,

\[ AP(q, N) = \frac{\sum_{i=1}^{N} P(q, i)}{N} \]

which indicates that the higher the relevant documents are ranked, the larger AP@N will be. Unless stated to the contrary, the evaluation metrics shown in this paper are the average for all 50 queries. For comparison, as mentioned in Section 2, we also implemented two baseline algorithms gGloss(0) [10] and IS-Cluster [27] that were shown to be very effective.

B. Experimental Results

In the experiments, we first evaluate the performance of C-DLSI and study the impacts of each parameter. Then we analyze the compatibility issue for C-DLSI in FTR. Next, we compare our method, denoted as C-DLSI(\( \epsilon \)), with another form of C-DLSI which is based on a truncated value \( k \), namely, C-DLSI(\( k \)). Finally, we examine the performance of the collection update algorithm. Since FTR usually selects a
small number of peers, we focus more on the performance for small cast numbers (e.g., $T \leq 25$) in the experiments.

1) Performance Evaluation: At the beginning, the descriptors of all 50 peers are stored in the broker. During the experiments, the broker will load the short queries extracted from TREC topics 301 – 350 and perform peer selection and final result merging. Table 3 presents the peer selection results for each approach, where the setting of C-DLSI is $K = 20$, $\varepsilon = 5$, and $h = 10$. The comparison criterion is based on the number of relevant documents contained in the selected peers. Comp0 and Comp1 compare C-DLSI with gGloss(0) and IS-Cluster respectively, by measuring the portion of the queries in which one method outperforms the other. Specifically, $>$ means C-DLSI outperforms gGloss(0) (IS-Cluster), while $<$ denotes the reverse. Avg. Recall denotes the average recall of the selected peers for all of the 50 queries. We can see that C-DLSI as a whole outperforms gGloss(0) and is close to IS-Cluster. Similar results can be observed for other settings.

For performance comparison, Figure 5 and Figure 6 show the top-N precision (P@N) and top-N average precision (AP@N) of all three methods for increasing cast number under two different settings. We can see that C-DLSI with a proper threshold $\varepsilon$ (discussed in Section 5.2.2), e.g., $\varepsilon = 5.5$ for cluster number $K = 10$, in general outperforms the other two methods under both evaluation metrics. To understand these results further, we check the characteristics of the peers in the simulation. Specifically, the gray-scale map of a peer for $K = 20$ is given in Figure 7. In this map, some popular terms are removed. It shows that the TREC data used in the experiments is relatively sparse, which means it is generally difficult to properly rank them. Besides, it leads to unsatisfactory clustering results. Based on this, we can only expect a modest improvement by applying C-DLSI on this dataset. Note that we use different collection assignments in two experiments to gain a general conclusion. The determination of parameters is discussed in Section 5.2.2. Since the performance of C-DLSI in different collection assignments in general are similar, we mainly utilize the collection assignment of $K = 20$ as an example to investigate the properties of C-DLSI in the following experiments.

2) Impacts of Parameters:

Number of relevant clusters $h$: In C-DLSI, only $top - h$ relevant clusters are used to judge the relevance of a collection (see Section 4.5). Figure 8 shows the performance of C-DLSI with different $h$ values for cast number 5, 10, 15, 20, 25 and 30. From the results, we can see that for the smallest number
For each peer searches the optimal threshold $\varepsilon$ independently. Based on the metric of AP@10, each peer searches the optimal threshold $\varepsilon$ from the testing interval between 1 and 9, which finally concentrates on either 1 or 5. From the results, we can see that this threshold decision method causes a slight performance decrease compared to the optimal case of $\varepsilon = 5$ but still outperforms the other methods such as IS-Cluster. Generally, how to automatically decide the proper $\varepsilon$ value for each peer and achieve a global optimal performance remains an open question to be answered in our future work.

Cluster number $K$: In general, the quality of k-means clustering is determined by the preset cluster number $K$. To examine how much the FTR approaches rely on the clustering quality, we investigate the performance of the three methods with different cluster numbers, as presented in Figure 11 (each cluster number corresponds to a different collection assignment). The results show that IS-Cluster is more sensitive to the cluster number. For larger cluster number $K$ (e.g., $K = 20$ or $30$), IS-Cluster outperforms gGloss(0). However, for small cluster number $K$ (e.g., $K = 10$), IS-Cluster may be beaten by gGloss(0). It indicates that IS-Cluster relies more on the clustering quality and we have to select proper $K$ to guarantee a good performance. On the contrary, C-DLSI is more stable and substantially outperforms gGloss(0) most of the time. This characteristic means a lot since the
IS-Cluster and LSI-based text retrieval is also a good choice. Based on this, we may consider whether a combination of uses IS-Cluster. Figure 12 shows the result of this comparison. However, for peer selection, CM1 uses gGloss(0) while CM2 retrieve documents in each peer based on LSI as in C-DLSI.

Combination methods, namely CM1 and CM2. Both of them point out in Section 4.1), thus achieving little improvement. Therefore, the performance of the combination method CM2 is only slightly better than CM1. However, the peer selection method of C-DLSI can distinguish each document and obtain proper semantic spaces based on LSI. Therefore, it is more adaptive to the LSI-based text retrieval.

4) C-DLSI($\varepsilon$) vs. C-DLSI($k$): In this subsection, we compare our method C-DLSI, denoted as C-DLSI($\varepsilon$), with another possible form of C-DLSI which is based on a truncated number $k$, namely, C-DLSI($k$). Here we choose the truncated value $k$ with the best performance of all possible values for C-DLSI, e.g., $k = 80$ for the case $K = 20$, and $k = 60$ for the case $K = 10$. The results are shown in Figure 13 and Figure 14 for the cases $K = 20$ and $K = 10$ respectively. We can see that C-DLSI($\varepsilon$) in general beats C-DLSI($k$). In particular, for the case $K = 10$, when all of the indexing peers are selected ($G = 50$), this gap becomes largest, indicating an 11.63% improvement over C-DLSI($k$). We find that the numbers of the relevant documents returned by the peers in two methods are quite similar. It means C-DLSI($\varepsilon$) makes the LSI spaces among clusters comparable and thus provides better result merging. Finally, we also examine the C-DLSI scheme without considering the cluster relations, denoted as C-DLSI-NR($\varepsilon$). The performance are given in Figure 13 and Figure 14. Generally, by considering cluster relations, C-DLSI($\varepsilon$) gains some improvements compared to C-DLSI-NR($\varepsilon$). This gain becomes larger for $K = 20$, because the clustering quality in the case $K = 20$ is worse than that of $K = 10$ (as shown in Figure 15).

5) Collection Update Scheme: Finally, we will test our update scheme in FTR. In the experiment, we only simulate one case of collection update, i.e., indexing new documents. Specifically, we first index only 70% of the total documents and build the corresponding LSI. Then we gradually add new documents from the remaining set, adding 5% of the indexed size in each step. Figure 16 shows an example ($K = 10$, $N = 10$) of the performance variation of the three methods during the update procedure. We can see that the performance of C-DLSI still increases with more documents added. For small cast number (e.g., $T = 10$), C-DLSI outperforms (or at least be comparable to) gGloss(0) (IS-Cluster) until the update amount reaches $30\% - 35\% (5\% - 10\%)$. For larger cast number (e.g., $T = 20$), this valid amount for C-DLSI before rebuilding the LSI decreases to $10\% - 15\% (5\% - 10\%)$. Besides, we also
get similar results for other settings. It means that our update scheme is especially applicable for FTR systems, in which the cast number is relatively small.

VI. CONCLUSION

In this paper, we proposed a promising solution for the challenges of FTR. Different from the existing methods, our proposed method, Cluster-based Distributed Latent Semant

ic Indexing (C-DLSI), captures the semantic structure of a peer by identifying the LSI spaces within the clusters and considering the relations among them, thus providing more precise evaluation of the peer. We analyzed the characteristics of C-DLSI, based on which novel descriptors of the peers and the federated query processing was proposed. Besides, we devised an effective form of C-DLSI, namely, C-DLSI(ε), the performance of which is studied and verified by using grayscale map in the experiments. Our method is efficient since only the clusters affected by the updates need to be reindexed. Moreover, we consider the update problem of C-DLSI and provide an update scheme to make the framework more efficient while guaranteeing its effectiveness. The experimental results confirmed the superiority of our model and update scheme, and showed that our method outperforms other existing methods including the previous cluster-based method.

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