Best Keyword Cover Search

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Abstract—It is common that the objects in a spatial database (e.g., restaurants/hotels) are associated with keyword(s) to indicate their businesses/services/features. An interesting problem known as *Closest Keywords* search is to query objects, called *keyword cover*, which together cover a set of query keywords and have the minimum inter-objects distance. In recent years, we observe the increasing availability and importance of keyword rating in object evaluation for the better decision making. This motivates us to investigate a generic version of *Closest Keywords* search called *Best Keyword Cover* which considers inter-objects distance as well as the keyword rating of objects. The baseline algorithm is inspired by the methods of *Closest Keywords* search which is based on exhaustively combining objects from different query keywords to generate candidate keyword covers. When the number of query keywords increases, the performance of the baseline algorithm drops dramatically as a result of massive candidate keyword covers generated. To attack this drawback, this work proposes a much more scalable algorithm called *keyword nearest neighbor expansion* (keyword-NNE). Compared to the baseline algorithm, keyword-NNE algorithm significantly reduces the number of candidate keyword covers generated. The in-depth analysis and extensive experiments on real data sets have justified the superiority of our keyword-NNE algorithm.

Index Terms—Spatial database, point of interests, keywords, keyword rating, keyword cover

1 Introduction

Driven by mobile computing, location-based services and wide availability of extensive digital maps and satellite imagery (e.g., Google Maps and Microsoft Virtual Earth services), the *spatial keywords search* problem has attracted much attention recently [3], [4], [5], [7], [8], [10], [15], [16], [18].

In a spatial database, each tuple represents a spatial object which is associated with keyword(s) to indicate the information such as its businesses/services/features. Given a set of query keywords, an essential task of spatial keywords search is to identify spatial object(s) which are associated with keywords relevant to a set of query keywords, and have desirable spatial relationships (e.g., close to each other and/or close to a query location). This problem has unique value in various applications because users' requirements are often expressed as multiple keywords. For example, a tourist who plans to visit a city may have particular shopping, dining and accommodation needs. It is desirable that all these needs can be satisfied without long distance traveling.

Due to the remarkable value in practice, several variants of spatial keyword search problem have been studied. The works [5], [7], [8], [15] aim to find a number of individual objects, each of which is close to a query location and the associated keywords (or called *document*) are very relevant to a set of query keywords (or called *query document*). The document similarity (e.g., [14]) is applied to measure the relevance between two sets of keywords. Since it is likely none of individual objects is associated with all query keywords, this motivates the studies [4], [17], [18] to retrieve multiple objects, called *keyword cover*, which together cover (i.e., associated with) all query keywords and are close to each other. This problem is known as m *Closest Keywords* (mCK) query in [17], [18]. The problem studied in [4] additionally requires the retrieved objects close to a query location.

This paper investigates a generic version of mCK query, called *Best Keyword Cover* (*BKC*) query, which considers inter-objects distance as well as keyword rating. It is motivated by the observation of increasing availability and importance of keyword rating in decision making. Millions of businesses/services/features around the world have been rated by customers through online business review sites such as Yelp, Citysearch, ZAGAT and Dianping, etc. For example, a restaurant is rated 65 out of 100 (ZAGAT.com) and a hotel is rated 3.9 out of 5 (hotels.com). According to a survey in 2013 conducted by Dimensional Research (dimensionalresearch.com), an overwhelming 90 percent of respondents claimed that buying decisions are influenced by online business review/rating. Due to the consideration of keyword rating, the solution of *BKC* query can be very different from that of mCK query. Fig. 1 shows an example. Suppose the query keywords are "Hotel", "Restaurant" and "Bar". mCK query returns $\{t_2, s_2, c_2\}$ since it considers the distance between the returned objects only. *BKC* query returns $\{t_1, s_1, c_1\}$ since the keyword ratings of object are considered in addition to the inter-objects distance. Compared to mCK query, *BKC* query supports more robust object evaluation and thus underpins the better decision making.

This work develops two *BKC* query processing algorithms, *baseline* and *keyword-NNE*. The baseline algorithm is inspired by the mCK query processing methods [17], [18]. Both the *baseline* algorithm and *keyword-NNE* algorithm are supported by indexing the objects with an R*-tree like index, called *KRR*-tree*. In the baseline algorithm, the

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Manuscript received 9 July 2013; revised 27 Apr. 2014; accepted 8 May 2014. Date of publication 22 May 2014; date of current version 1 Dec. 2014. Recommended for acceptance by J. Sander.
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below.
Digital Object Identifier no. 10.1109/TKDE.2014.2324897

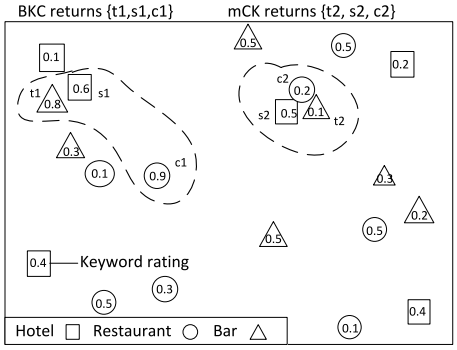


Fig. 1. BKC versus mCK.

idea is to combine nodes in higher hierarchical levels of KRR*-trees to generate candidate keyword covers. Then, the most promising candidate is assessed in priority by combining their child nodes to generate new candidates. Even though BKC query can be effectively resolved, when the number of query keywords increases, the performance drops dramatically as a result of massive candidate keyword covers generated.

To overcome this critical drawback, we developed much scalable *keyword nearest neighbor expansion* (keyword-NNE) algorithm which applies a different strategy. Keyword-NNE selects one query keyword as *principal query keyword*. The objects associated with the principal query keyword are *principal objects*. For each principal object, the local best solution (known as *local best keyword cover* (*lbkc*)) is computed. Among them, the $lbkc$ with the highest evaluation is the solution of BKC query. Given a principal object, its $lbkc$ can be identified by simply retrieving a few nearby and highly rated objects in each non-principal query keyword (two-four objects in average as illustrated in experiments). Compared to the baseline algorithm, the number of candidate keyword covers generated in keyword-NNE algorithm is significantly reduced. The in-depth analysis reveals that the number of candidate keyword covers further processed in keyword-NNE algorithm is optimal, and each keyword candidate cover processing generates much less new candidate keyword covers than that in the baseline algorithm.

In the remainder of this paper, the problem is defined in Section 2 and the related work is reviewed in Section 3. Section 4 discusses keyword rating R*-tree. The baseline algorithm and keyword-NNE algorithm are introduced in Sections 5 and 6, respectively. Section 7 discusses the situation of weighted average of keyword ratings. An in-depth analysis is given in Section 8. Then Section 9 reports the experimental results. The paper is concluded in Section 10.

2 Preliminary

Given a spatial database, each object may be associated with one or multiple keywords. Without loss of generality, the object with multiple keywords are transformed to multiple objects located at the same location, each with a distinct single keyword. So, an object is in the form $\langle id, x, y, keyword, rating\rangle$ where x, y define the location of the object in a two-dimensional geographical space. No data quality problem such as misspelling exists in keywords.

Definition 1 (Diameter). *Let O be a set of objects $\{o_1, \ldots, o_n\}$. For $o_i, o_j \in O$, $dist(o_i, o_j)$ is the euclidean distance between o_i, o_j in the two-dimensional geographical space. The diameter of O is*

$$diam(O) = \max_{o_i, o_j \in O} dist(o_i, o_j). \quad (1)$$

The score of O is a function with respect to not only the diameter of O but also the keyword rating of objects in O. Users may have different interests in keyword rating of objects. We first discuss the situation that a user expects to maximize the minimum keyword rating of objects in BKC query. Then we will discuss another situation in Section 7 that a user expects to maximize the weighted average of keyword ratings.

The linear interpolation function [5], [16] is used to obtain the score of O such that the score is a linear interpolation of the individually normalized diameter and the minimum keyword rating of O.

$$\begin{aligned} O.score &= score(A, B) \\ &= \alpha\left(1 - \frac{A}{max\_dist}\right) + (1-\alpha)\frac{B}{max\_rating}. \\ A &= diam(O). \\ B &= \min_{o \in O}(o.rating), \end{aligned} \quad (2)$$

where B is the minimum keyword rating of objects in O and $\alpha (0 \le \alpha \le 1)$ is an application specific parameter. If $\alpha = 1$, the score of O is solely determined by the diameter of O. In this case, BKC query is degraded to mCK query. If $\alpha = 0$, the score of O only considers the minimum keyword rating of objects in Q where max_dist and max_rating are used to normalize diameter and keyword rating into [0, 1] respectively. max_dist is the maximum distance between any two objects in the spatial database D, and max_rating is the maximum keyword rating of objects.

Lemma 1. *The score is of monotone property.*

Proof. Given a set of objects O_i, suppose O_j is a subset of O_i. The diameter of O_i must be not less than that of O_j, and the minimum keyword rating of objects in O_i must be not greater than that of objects in O_j. Therefore, $O_i.score \le O_j.score$. □

Definition 2 (Keyword Cover). *Let T be a set of keywords $\{k_1, \ldots, k_n\}$ and O a set of objects $\{o_1, \ldots, o_n\}$, O is a keyword cover of T if one object in O is associated with one and only one keyword in T.*

Definition 3 (Best Keyword Cover Query). *Given a spatial database D and a set of query keywords T, BKC query returns a keyword cover O of T $(O \subset D)$ such that $O.score \ge O'.score$ for any keyword cover O' of T $(O' \subset D)$.*

The notations used in this work are summarized in Table 1.

3 Related Work

3.1 Spatial Keyword Search

Recently, the spatial keyword search has received considerable attention from research community. Some existing works focus on retrieving individual objects by specifying

TABLE 1
Summary of Notations

Notation	Interpretation
D	A spatial database.
T	A set of query keywords.
O_k	The set of objects associated with keyword k.
o_k	An object in O_k.
KC_o	The set of keyword covers in each of which o is a member.
kc_o	A keyword cover in KC_o.
$lbkc_o$	The local best keyword cover of o, i.e., the keyword cover in KC_o with the highest score.
$o_k.NN^n_{ki}$	o_k's n^{th} keyword nearest neighbor in query keyword k_i.
KRR*$_k$-tree	The keyword rating R*-tree of O_k.
N_k	A node of KRR*$_k$-tree.

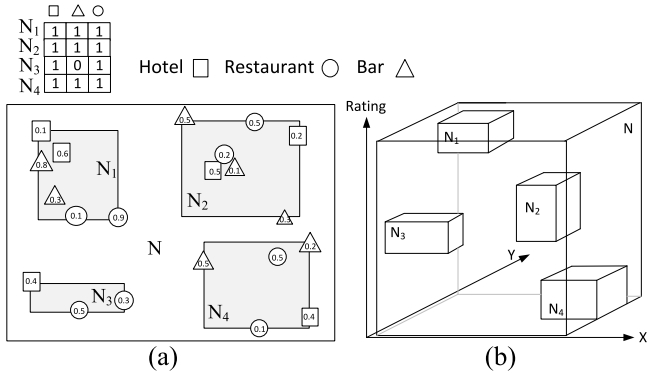


Fig. 2. (a) A bR*-tree. (b) The KRR*-tree for keyword "restaurant".

a query consisting of a query location and a set of query keywords (or known as *document* in some context). Each retrieved object is associated with keywords relevant to the query keywords and is close to the query location [3], [5], [7], [8], [10], [15], [16]. The similarity between documents (e.g., [14]) are applied to measure the relevance between two sets of keywords.

Since it is likely no individual object is associated with all query keywords, some other works aim to retrieve multiple objects which together cover all query keywords [4], [17], [18]. While potentially a large number of object combinations satisfy this requirement, the research problem is that the retrieved objects must have desirable spatial relationship. In [4], authors put forward the problem to retrieve objects which 1) cover all query keywords, 2) have minimum inter-objects distance and 3) are close to a query location. The work [17], [18] study a similar problem called m Closet Keywords (mCK). mCK aims to find objects which cover all query keywords and have the minimum inter-objects distance. Since no query location is asked in mCK, the search space in mCK is not constrained by the query location. The problem studied in this paper is a generic version of mCK query by also considering keyword rating of objects.

3.2 Access Methods

The approaches proposed by Cong et al. [5] and Li et al. [10] employ a hybrid index that augments nodes in non-leaf nodes of an R/R*-tree with inverted indexes. The inverted index at each node refers to a pseudo-document that represents the keywords under the node. Therefore, in order to verify if a node is relevant to a set of query keywords, the inverted index is accessed at each node to evaluate the matching between the query keywords and the pseudo-document associated with the node.

In [18], bR*-tree was proposed where a bitmap is kept for each node instead of pseudo-document. Each bit corresponds to a keyword. If a bit is "1", it indicates some object(s) under the node is associated with the corresponding keyword; "0" otherwise. A bR*-tree example is shown in Fig. 2a where a non-leaf node N has four child nodes N_1, N_2, N_3, and N_4. The bitmaps of N_1, N_2, N_4 are 111 and the bitmap of N_3 is 101. In specific, the bitmap 101 indicates some objects under N_3 are associated with keyword "hotel" and "restaurant" respectively, and no object under N_3 is associated with keyword "bar". The bitmap allows to combine nodes to generate candidate keyword covers. If a node contains all query keywords, this node is a candidate keyword cover. If multiple nodes together cover all query keywords, they constitute a candidate keyword cover. Suppose the query keywords are 111. When N is visited, its child node N_1, N_2, N_3, N_4 are processed. N_1, N_2, N_4 are associated with all query keywords and N_3 is associated with two query keywords. The candidate keyword covers generated are $\{N_1\}$, $\{N_2\}$, $\{N_4\}$, $\{N_1, N_2\}$, $\{N_1, N_3\}$, $\{N_1, N_4\}$, $\{N_2, N_3\}$, $\{N_2, N_4\}$, $\{N_3, N_4\}$, $\{N_1, N_2, N_3\}$, $\{N_1, N_3, N_4\}$ and $\{N_2, N_3, N_4\}$. Among the candidate keyword covers, the one with the best evaluation is processed by combining their child nodes to generate more candidates. However, the number of candidates generated can be very large. Thus, the depth-first bR*-tree browsing strategy is applied in order to access the objects in leaf nodes as soon as possible. The purpose is to obtain the current best solution as soon as possible. The current best solution is used to prune the candidate keyword covers. In the same way, the remaining candidates are processed and the current best solution is updated once a better solution is identified. When all candidates have been pruned, the current best solution is returned to mCK query.

In [17], a virtual bR*-tree based method is introduced to handle mCK query with attempt to handle data set with massive number of keywords. Compared to the method in [18], a different index structure is utilized. In virtual bR*-tree based method, an R*-tree is used to index locations of objects and an inverted index is used to label the leaf nodes in the R*-tree associated with each keyword. Since only leaf nodes have keyword information the mCK query is processed by browsing index bottom-up. At first, m inverted lists corresponding to the query keywords are retrieved, and fetch all objects from the same leaf node to construct a virtual node in memory. Clearly, it has a counterpart in the original R*-tree. Each time a virtual node is constructed, it will be treated as a subtree which is browsed in the same way as in [18]. Compared to bR*-tree, the number of nodes in R*-tree has been greatly reduced such that the I/O cost is saved.

As opposed to employing a single R*-tree embedded with keyword information, multiple R*-trees have been used to process multiway spatial join (MWSJ) which involves data of different keywords (or types). Given a

number of R*-trees, one for each keyword, the MWSJ technique of Papadias et al. [13] (later extended by Mamoulis and Papadias [11]) uses the synchronous R*-tree approach [2] and the window reduction (WR) approach [12]. Given two R*-tree indexed relations, SRT performs two-way spatial join via synchronous traversal of the two R*-trees based on the property that if two intermediate R*-tree nodes do not satisfy the spatial join predicate, then the MBRs below them will not satisfy the spatial predicate either. WR uses window queries to identify spatial regions which may contribute to MWSJ results.

4 Indexing Keyword Ratings

To process BKC query, we augment R*-tree with one additional dimension to index keyword ratings. Keyword rating dimension and spatial dimension are inherently different measures with different ranges. It is necessary to make adjustment. In this work, a three-dimensional R*-tree called *keyword rating R*-tree* (KRR*-tree) is used. The ranges of both spatial and keyword rating dimensions are normalized into [0, 1]. Suppose we need construct a KRR*-tree over a set of objects D. Each object $o \in D$ is mapped into a new space using the following mapping function:

$$f : o(x, y, rating) \rightarrow o\left(\frac{x}{max_x}, \frac{y}{max_y}, \frac{rating}{max\_rating}\right), \quad (3)$$

where max_x, max_y, max_rating are the maximum value of objects in D on x, y and keyword rating dimensions respectively. In the new space, KRR*-tree can be constructed in the same way as constructing a conventional three-dimensional R*-tree. Each node N in KRR*-tree is defined as $N(x, y, r, l_x, l_y, l_r)$ where x is the value of N in x axle close to the origin, i.e., (0, 0, 0, 0, 0, 0), and l_x is the width of N in x axle, so do y, l_y and r, l_r. The Fig. 2b gives an example to illustrate the nodes of KRR*-tree indexing the objects in keyword "restaurant".

In [17], [18], a single tree structure is used to index objects of different keywords. In the similar way as discussed above, the single tree can be extended with an additional dimension to index keyword rating. A single tree structure suits the situation that most keywords are query keywords. For the above mentioned example, all keywords, i.e., "hotel", "restaurant" and "bar", are query keywords. However, it is more frequent that only a small fraction of keywords are query keywords. For example in the experiments, only less than 5 percent keywords are query keywords. In this situation, a single tree is poor to approximate the spatial relationship between objects of few specific keywords. Therefore, multiple KRR*-trees are used in this work, each for one keyword.[1] The KRR*-tree for keyword k_i is denoted as KRR*$_{ki}$-tree.

Given an object, the rating of an associated keyword is typically the mean of ratings given by a number of customers for a period of time. The change does happen but slowly. Even though dramatic change occurs, the KRR*-tree is updated in the standard way of R*-tree update.

1. If the total number of objects associated with a keyword is very small, no index is needed for this keyword and these objects are simply processed one by one.

5 Baseline Algorithm

The baseline algorithm is inspired by the mCK query processing methods [17], [18]. For mCK query processing, the method in [18] browses index in top-down manner while the method in [17] does bottom-up. Given the same hierarchical index structure, the top-down browsing manner typically performs better than the bottom-up since the search in lower hierarchical levels is always guided by the search result in the higher hierarchical levels. However, the significant advantage of the method in [17] over the method in [18] has been reported. This is because of the different index structures applied. Both of them use a single tree structure to index data objects of different keywords. But the number of nodes of the index in [17] has been greatly reduced to save I/O cost by keeping keyword information with inverted index separately. Since only leaf nodes and their keyword information are maintained in the inverted index, the bottom-up index browsing manner is used. When designing the baseline algorithm for BKC query processing, we take the advantages of both methods [17], [18]. First, we apply multiple KRR*-trees which contain no keyword information in nodes such that the number of nodes of the index is not more than that of the index in [17]; second, the top-down index browsing method can be applied since each keyword has own index.

Suppose KRR*-trees, each for one keyword, have been constructed. Given a set of query keywords $T = \{k_1, \ldots, k_n\}$, the child nodes of the root of KRR*$_{ki}$-tree ($i \leq i \leq n$) are retrieved and they are combined to generate candidate keyword covers. Given a candidate keyword cover $O = \{N_{k1}, \ldots, N_{kn}\}$ where N_{ki} is a node of KRR*$_{ki}$-tree.

$$\begin{aligned} O.score &= score(A, B). \\ A &= \max_{N_i, N_j \in O} dist(N_i, N_j) \\ B &= \min_{N \in O}(N.maxrating), \end{aligned} \quad (4)$$

where $N.maxrating$ is the maximum value of objects under N in keyword rating dimension; $dist(N_i, N_j)$ is the minimum euclidean distance between N_i and N_j in the two-dimensional geographical space defined by x and y dimensions.

Lemma 2. *Given two keyword covers O and O', O' consists of objects $\{o_{k1}, \ldots, o_{kn}\}$ and O consists of nodes $\{N_{k1}, \ldots, N_{kn}\}$. If o_{ki} is under N_{ki} in KRR*$_{ki}$-tree for $1 \leq i \leq n$, it is true that $O'.score \leq O.score$.*

Algorithm 1 shows the pseudo-code of the baseline algorithm. Given a set of query keywords T, it first generates candidate keyword covers using $Generate\_Candidate$ function which combines the child nodes of the roots of KRR*$_{ki}$-trees for all $k_i \in T$ (line 2). These candidates are maintained in a heap H. Then, the candidate with the highest score in H is selected and its child nodes are combined using $Generate\_Candidate$ function to generate more candidates. Since the number of candidates can be very large, the depth-first KRR*$_{ki}$-tree browsing strategy is applied to access the leaf nodes as soon as possible (line 6). The first candidate consisting of objects (not nodes of KRR*-tree) is

the current best solution, denoted as bkc, which is an intermediate solution. According to Lemma 2, the candidates in H are pruned if they have $score$ less than $bkc.score$ (line 8). The remaining candidates are processed in the same way and bkc is updated if the better intermediate solution is found. Once no candidate is remained in H, the algorithm terminates by returning current bkc to BKC query.

Algorithm 1. $Baseline(T, Root)$

Input: A set of query keywords T, the root nodes of all KRR*-trees $Root$.
Output: Best Keyword Cover.
1: $bkc \leftarrow \emptyset$;
2: $H \leftarrow Generate\_Candidate(T, Root, bkc)$;
3: **while** H *is not empty* **do**
4: $can \leftarrow$ the candidate in H with the highest score;
5: Remove can from H;
6: $Depth\_First\_Tree\_Browsing(H, T, can, bkc)$;
7: **foreach** $candidate \in H$ **do**
8: **if** $(candidate.score \leq bkc.score)$ **then**
9: remove $candidate$ from H;
10: **return** bkc;

Algorithm 2. $Depth\_First\_Tree\_Browsing\ (H, T, can, bkc)$

Input: A set of query keywords T, a candidate can, the candidate set H, and the current best solution bkc.
1: **if** can *consists of leaf nodes* **then**
2: $S \leftarrow$ objects in can;
3: $bkc' \leftarrow$ the keyword cover with the highest score identified in S;
4: **if** $bkc.score < bkc'.score$ **then**
5: $bkc \leftarrow bkc'$;
6: **else**
7: $New\_Cans \leftarrow Generate\_Candidate(T, can, bkc)$;
8: Replace can by New_Cans in H;
9: $can \leftarrow$ the candidate in New_Cans with the highest score;
10: $Depth\_First\_Tree\_Browsing(H, T, can, bkc)$;

In $Generate\_Candidate$ function, it is unnecessary to actually generate all possible keyword covers of input nodes (or objects). In practice, the keyword covers are generated by incrementally combining individual nodes (or objects). An example in Fig. 3 shows all possible combinations of input nodes incrementally generated bottom up. There are three keywords k_1, k_2 and k_3 and each keyword has two nodes. Due to the monotonic property in Lemma 1, the idea of Apriori algorithm [1] can be applied. Initially, each node is a combination with $score = \infty$. The combination with the highest score is always processed in priority to combine one more input node in order to cover a keyword, which is not covered yet. If a combination has $score$ less than $bkc.score$, any superset of it must have $score$ less than $bkc.score$. Thus, it is unnecessary to generate the superset. For example, if $\{N2_{k2}, N2_{k3}\}.score < bkc.score$, any superset of $\{N2_{k2}, N2_{k3}\}$ must has $score$ less than $bkc.score$. So, it is not necessary to generate $\{N2_{k2}, N2_{k3}, N1_{k1}\}$ and $\{N2_{k2}, N2_{k3}, N2_{k1}\}$.

Algorithm 3. $Generate\_Candidate(T, can, bkc)$

Input: A set of query keywords T, a candidate can, the current best solution bkc.
Output: A set of new candidates.
1: $New\_Cans \leftarrow \emptyset$;
2: $COM \leftarrow$ combining child nodes of can to generate keyword covers;
3: **foreach** $com \in COM$ **do**
4: **if** $com.score > bkc.score$ **then**
5: $New\_Cans \leftarrow com$;
6: **return** New_Cans;

6 Keyword Nearest Neighbor Expansion

Using the baseline algorithm, BKC query can be effectively resolved. However, it is based on exhaustively combining objects (or their MBRs). Even though pruning techniques have been explored, it has been observed that the performance drops dramatically, when the number of query keywords increases, because of the fast increase of candidate keyword covers generated. This motivates us to develop a different algorithm called *keyword nearest neighbor expansion*.

We focus on a particular query keyword, called *principal query keyword*. The objects associated with the principal query keyword are called *principal objects*. Let k be the principal query keyword. The set of principle objects is denoted as O_k.

Definition 4 (Local Best Keyword Cover). *Given a set of query keywords T and the principal query keyword $k \in T$, the* local best keyword cover *of a principal object o_k is*

$$lbkc_{ok} = \Big\{ kc_{ok} \mid kc_{ok} \in KC_{ok}, \; kc_{ok}.score = \max_{kc \in KC_{ok}} kc.score \Big\}, \tag{5}$$

where KC_{ok} is the set of keyword covers in each of which the principal object o_k is a member.

For each principal object $o_k \in O_k$, $lbkc_{ok}$ is identified. Among all principal objects, the $lbkc_{ok}$ with the highest score is called *global best keyword cover* ($GBKC_k$).

Lemma 3. *$GBKC_k$ is the solution of BKC query.*

Proof. Assume the solution of BKC query is a keyword cover kc other than $GBKC_k$, i.e., $kc.score > GBKC_k.score$. Let o_k be the principal object in kc. By definition, $lbkc_{ok}.score \geq kc.score$, and $GBKC_k.score \geq lbkc_{ok}.score$. So, $GBKC_k.score \geq kc.score$ must be true. This conflicts to the assumption that BKC is a keyword cover kc other than $GBKC_k$. □

The sketch of keyword-NNE algorithm is as follows:

Sketch of Keyword-NNE Algorithm

Step 1. One query keyword $k \in T$ is selected as the principal query keyword;
Step 2. For each principal object $o_k \in O_k$, $lbkc_{ok}$ is computed;
Step 3. In O_k, $GBKC_k$ is identified;
Step 4. return $GBKC_k$.

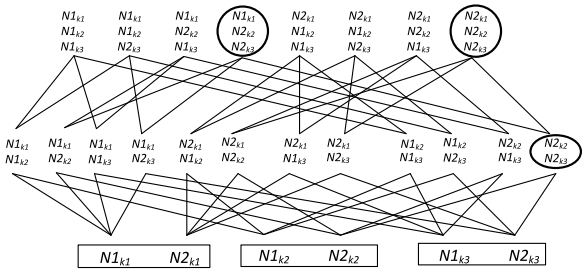


Fig. 3. Generating candidates.

Conceptually, any query keyword can be selected as the principal query keyword. Since computing *lbkc* is required for each principal object, the query keyword with the minimum number of objects is selected as the principal query keyword in order to achieve high performance.

6.1 LBKC Computation

Given a principal object o_k, $lbkc_{ok}$ consists of o_k and the objects in each non-principal query keyword which is close to o_k and have high keyword ratings. It motivates us to compute $lbkc_{ok}$ by incrementally retrieving the *keyword nearest neighbors* of o_k.

6.1.1 Keyword Nearest Neighbor

Definition 5 (Keyword Nearest Neighbor (Keyword-NN)). *Given a set of query keywords T, the principal query keyword is $k \in T$ and a non-principal query keyword is $k_i \in T/\{k\}$. O_k is the set of principal objects and O_{ki} is the set of objects of keyword k_i. The keyword nearest neighbor of a principal object $o_k \in O_k$ in keyword k_i is $o_{ki} \in O_{ki}$ iif $\{o_k, o_{ki}\}.score \geq \{o_k, o'_{ki}\}.score$ for all $o'_{ki} \in O_{ki}$.*

The first keyword-NN of o_k in keyword k_i is denoted as $o_k.nn^1_{ki}$ and the second keyword-NN is $o_k.nn^2_{ki}$, and so on. These keyword-NNs can be retrieved by browsing KRR*$_{ki}$-tree. Let N_{ki} be a node in KRR*$_{ki}$-tree.

$$\begin{aligned} \{o_k, N_{ki}\}.score &= score(A, B). \\ A &= dist(o_k, N_{ki}.) \\ B &= \min(N_{ki}.maxrating, o_k.rating), \end{aligned} \tag{6}$$

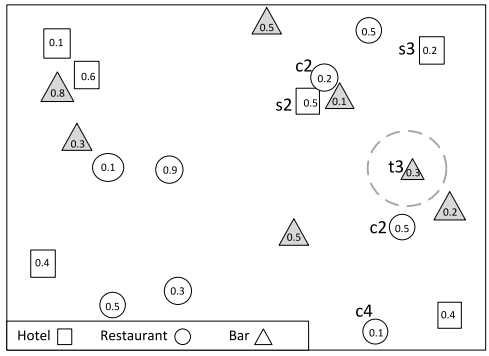
where $dist(o_k, N_{ki})$ is the minimum distance between o_k and N_{ki} in the two-dimensional geographical space defined by x and y dimensions, and $N_{ki}.maxrating$ is the maximum value of N_{ki} in keyword rating dimension.

Lemma 4. *For any object o_{ki} under node N_{ki} in KRR*$_{ki}$-tree,*

$$\{o_k, N_{ki}\}.score \geq \{o_k, o_{ki}\}.score. \tag{7}$$

Proof. It is a special case of Lemma 2. □

To retrieve keyword-NNs of a principal object o_k in keyword k_i, KRR*$_{ki}$-tree is browsed in the best-first strategy [9]. The root node of KRR*$_{ki}$-tree is visited first by keeping its child nodes in a heap H. For each node $N_{ki} \in H$, $\{o_k, N_{ki}\}.score$ is computed. The node in H with the highest $score$ is replaced by its child nodes. This operation is repeated until an object o_{ki} (not a KRR*$_{ki}$-tree node) is visited. $\{o_k, o_{ki}\}.score$ is denoted as $current\_best$ and o_k is the current best object.



Computing $lbkc_{t3}$

steps	Incrementally retrieve keyword-NN of t_3		S	$kc.score$
	"restaurant"	"hotel"		
1	$\{t_3, c_2\}.score = 0.7$	$\{t_3, s_3\}.score = 0.8$	t_3, s_3, c_2	0.3
2		$\{t_3, s_2\}.score = 0.28$	t_3, s_3, s_2, c_2	0.3
3	$\{t_3, c_3\}.score = 0.6$		t_3, s_3, s_2, c_2, c_3	0.4
4	$\{t_3, c_4\}.score = 0.35$		$t_3, s_3, s_2, c_2, c_3, c_4$	0.4

Fig. 4. An example of $lbkc$ computation.

According to Lemma 4, any node $N_{ki} \in H$ is pruned if $\{o_k, N_{ki}\}.score \leq current\_best$. When H is empty, the current best object is $o_k.nn^1_{ki}$. In the similar way, $o_k.nn^j_{ki}$ $(j > 1)$ can be identified.

6.1.2 $lbkc$ Computing Algorithm

Computing $lbkc_{ok}$ is to incrementally retrieve keyword-NNs of o_k in each non-principal query keyword. An example is shown in Fig. 4 where query keywords are "bar", "restaurant" and "hotel". The principal query keyword is "bar". Suppose we are computing $lbkc_{t3}$. The first keyword-NN of t_3 in "restaurant" and "hotel" are c_2 and s_3 respectively. A set S is used to keep t_3, s_3, c_2. Let kc be the keyword cover in S which has the highest score (the idea of Apriori algorithm can be used, see Section 5). After step 1, $kc.score = 0.3$. In step 2, "hotel" is selected and the second keyword-NN of t_3 in "hotel" is retrieved, i.e., s_2. Since $\{t_3, s_2\}.score < kc.score$, s_2 can be pruned and more importantly all objects not accessed in "hotel" can be pruned according to Lemma 5. In step 3, the second keyword-NN of t_3 in "restaurant" is retrieved, i.e., c_3. Since $\{t_3, c_3\}.score > kc.score$, c_3 is inserted into S. As a result, kc is updated to 0.4. Then, the third keyword-NN of t_3 in "restaurant" is retrieved, i.e., c_4. Since $\{t_3, c_4\}.score < kc.score$, c_4 and all objects not accessed yet in "restaurant" can be pruned according to Lemma 5. To this point, the current kc is $lbkc_{t3}$.

Lemma 5. *If $kc.score > \{o_k, o_k.nn^t_{ki}\}$, $o_k.nn^t_{ki}$ and $o_k.nn^{t'}_{ki}$ $(t' > t)$ must not be in $lbkc_{ok}$.*

Proof. By definition, $kc.score \leq lbkc_{ok}.score$. Since $\{o_k, o_k.nn^t_{ki}\}.score < kc.score$, we have $\{o_k, o_k.nn^t_{ki}\}.score < lbkc_{ok}.score$ and in turn $\{o_k, o_k.nn^{t'}_{ki}\}.score < lbkc_{ok}.score$. If $o_k.nn^t_{ki}$ is in $lbkc_{ok}$, $\{o_k, o_k.nn^t_{ki}\}.score \geq lbkc_{ok}.score$ according to Lemma 1, so is $o_k.nn^{t'}_{ki}$. Thus, $o_k.nn^t_{ki}$ and $o_k.nn^{t'}_{ki}$ must not be in $lbkc_{ok}$. □

For each non-principal query keyword k_i, after retrieving the first t keyword-NNs of o_k in keyword k_i, we use $k_i.score$ to denoted $\{o_k, o_k.nn^t_{ki}\}.score$. For example in Fig. 4,

"restaurant".$score$ is 0.7, 0.6 and 0.35 after retrieving the 1st, 2nd and 3rd keyword-NN of t_3 in "restaurant". According to Lemma 5, we have

Lemma 6. $lbkc_{ok} \equiv kc\ once\ kc.score > max_{k_i \in T/\{k\}}(k_i.score)$.

Algorithm 4. $Local\_Best\_Keyword\_Cover(o_k, T)$

Input: A set of query keywords T, a principal object o_k
Output: $lbkc_{ok}$

1: **foreach** *non-principal query keyword* $k_i \in T$ **do**
2: $S \leftarrow$ retrieve $o_k.nn^1_{ki}$;
3: $k_i.score \leftarrow \{o_k, o_k.nn^1_{ki}\}.score$;
4: $k_i.n = 1$;
5: $kc \leftarrow$ the keyword cover in S;
6: **while** $T \neq \emptyset$ **do**
7: Find $k_i \in T/\{k\}$, $k_i.score = \max_{k_j \in T/\{k\}}(k_j.score)$;
8: $k_i.n \leftarrow k_i.n + 1$;
9: $S \leftarrow S \cup$ retrieve $o_k.nn^{ki.n}_{ki}$;
10: $k_i.score \leftarrow \{o_k, o_k.nn^{ki.n}_{ki}\}.score$;
11: $temp\_kc \leftarrow$ the keyword cover in S;
12: **if** $temp\_kc.score > kc.score$ **then**
13: $kc \leftarrow temp\_kc$;
14: **foreach** $k_i \in T/\{k\}$ **do**
15: **if** $k_i.score \leq kc.score$ **then**
16: remove k_i from T;
17: **return** kc;

Algorithm 4 shows the pseudo-code of $lbkc_{ok}$ computing algorithm. For each non-principal query keyword k_i, the first keyword-NN of o_k is retrieved and $k_i.score = \{o_k, o_k.nn^1_{ki}\}.score$. They are kept in S and the best keyword cover kc in S is identified using $Generate\_Candidate$ function in Algorithm 3. The objects in different keywords are combined. Each time the most promising combination are selected to further do further combination until the best keyword cover is identified. When the second keyword-NN of o_k in k_i is retrieved, $k_i.score$ is updated to $\{o_k, o_k.nn^2_{ki}\}.score$, and so on. Each time one non-principal query keyword is selected to search next keyword-NN in it. Note that we always select keyword $k_i \in T/\{k\}$ where $k_i.score = max_{k_j \in T/\{k\}}(k_j.score)$ to minimize the number of keyword-NNs retrieved (line 7). After the next keyword-NN of o_k in this keyword is retrieved, it is inserted into S and kc is updated. If $k_i.score < kc.score$, all objects in k_i can be pruned by deleting k_i from T according to Lemma 5. When T is empty, kc is returned to $lbkc_{ok}$ according to Lemma 6.

6.2 Keyword-NNE Algorithm

In keyword-NNE algorithm, the principal objects are processed in blocks instead of individually. Let k be the principal query keyword. The principal objects are indexed using KRR*$_k$-tree. Given a node N_k in KRR*$_k$-tree, also known as a *principal node*, the local best keyword cover of N_k, $lbkc_{Nk}$, consists of N_k and the corresponding nodes of N_k in each non-principal query keyword.

Definition 6 (Corresponding Node). *N_k is a node of KRR*$_k$-tree at the hierarchical level i. Given a non-principal query keyword k_i, the corresponding nodes of N_k are nodes in KRR*$_{ki}$-tree at the hierarchical level i.*

The root of a KRR*-tree is at hierarchical level 1, its child nodes are at hierarchical level 2, and so on. For example, if N_k is a node at hierarchical level 4 in KRR*$_k$-tree, the corresponding nodes of N_k in keyword k_i are these nodes at hierarchical level 4 in KRR*$_{ki}$-tree. From the corresponding nodes, the keyword-NNs of N_k are retrieved incrementally for computing $lbkc_{Nk}$.

Lemma 7. *If a principal object o_k is an object under a principal node N_k in KRR*$_k$-tree*

$$lbkc_{Nk}.score \geq lbkc_{ok}.score.$$

Proof. Suppose $lbkc_{Nk} = \{N_k, N_{k1}, \ldots, N_{kn}\}$ and $lbkc_{ok} = \{o_k, o_{k1}, \ldots, o_{kn}\}$. For each non-principal query keyword k_i, o_{ki} is under a corresponding node of N_k, say N'_{ki}. Note that N'_{ki} can be in $lbkc_{Nk}$ or not. By definition,

$$lbkc_{Nk}.score \geq \{N_k, N'_{k1}, \ldots, N'_{kn}\}.score.$$

According to Lemma 2

$$\{N_k, N'_{k1}, \ldots, N'_{kn}\}.score \geq lbkc_{ok}.score.$$

So, we have

$$lbkc_{Nk}.score \geq lbkc_{ok}.score.$$

The lemma is proved. □

The pseudo-code of keyword-NNE algorithm is presented in Algorithm 5. Keyword-NNE algorithm starts by selecting a principal query keyword $k \in T$ (line 2). Then, the root node of KRR*$_k$-tree is visited by keeping its child nodes in a heap H. For each node N_k in H, $lbkc_{Nk}.score$ is computed (line 5). In H, the one with the maximum score, denoted as $H.head$, is processed. If $H.head$ is a node of KRR*$_k$-tree (lines 8-14), it is replaced in H by its child nodes. For each child node N_k, we compute $lbkc_{Nk}.score$. Correspondingly, $H.head$ is updated. If $H.head$ is a principle object o_k rather than a node in KRR*$_k$-tree (lines 15-21), $lbkc_{ok}$ is computed. If $lbkc_{ok}.score$ is greater than the score of the current best solution bkc ($bkc.score = 0$ initially), bkc is updated to be $lbkc_{ok}$. For any $N_k \in H$, N_k is pruned if $lbkc_{Nk}.score \leq bkc.score$ since $lbkc_{ok}.score \leq lbkc_{ok}$ for every o_k under N_k in KRR*$_k$-tree according to Lemma 7. Once H is empty, bkc is returned to BKC query.

Algorithm 5. $Keyword\text{-}NNE(T, D)$

Input: A set of query keywords T, a spatial database D
Output: Best Keyword Cover

1: $bkc.score \leftarrow 0$;
2: $k \leftarrow$ select the principal query keyword from T;
3: $H \leftarrow$ child nodes of the root in KRR*$_k$-tree;
4: **foreach** $N_k \in H$ **do**
5: Compute $lbkc_{Nk}.score$;
6: $H.head \leftarrow N_k \in H$ with $max_{N_k \in H}\ lbkc_{Nk}.score$;
7: **while** $H \neq \emptyset$ **do**
8: **while** $H.head$ is a node in KRR*$_k$-tree **do**
9: N $\leftarrow$ child nodes of $H.head$;
10: **foreach** N_k *in* N **do**

Compute $lbkc_{Nk}.score$;
Insert N_k into H;
Remove $H.head$ from H;
$H.head \leftarrow N_k \in H$ with $max_{N_k \in H} lbkc_{Nk}.score$;
/* $H.head$ is a principal object (i.e., not a node in KRR*$_k$-tree)*/
$o_k \leftarrow H.head$;
Compute $lbkc_{ok}.score$;
if $bkc.score < lbkc_{ok}.score$ **then**
  $bkc \leftarrow lbkc_{ok}$;
  foreach N_k *in* H **do**
    if $lbkc_{Nk}.score \leq bkc.score$ **then**
      Remove N_k from H;
return bkc;

7 Weighted Average of Keyword Ratings

To this point, the minimum keyword rating of objects in O is used in $O.score$. However, it is unsurprising that a user prefers the weighted average of keyword ratings of objects in O to measure $O.score$.

$$O.score = \alpha \times \left(1 - \frac{diam(O)}{max\_dist}\right) + (1-\alpha) \times \frac{W\_Average(O)}{max\_rating}, \tag{8}$$

where $W\_Average(O)$ is defined as

$$W\_Average(O) = \frac{\sum_{o_{ki} \in O} w_{ki} * o_{ki}.rating}{|O|}, \tag{9}$$

where w_{ki} is the weight associated with the query keyword k_i and $\sum_{k_i \in T} w_{ki} = 1$. For example, a user may give higher weight to "hotel" but lower weight to "restaurant" in a BKC query. Given the score function in Equation (8), the baseline algorithm and keyword-NNE algorithm can be used to process BKC query with minor modification. The core is to maintain the property in Lemmas 1 and in 2 which are the foundation of the pruning techniques in the baseline algorithm and the keyword-NNE algorithm.

However, the property in Lemma 1 is invalid given the score function defined in Equation (9). To maintain this property, if a combination does not cover a query keyword k_i, this combination is modified by inserting a virtual object associated with k_i. This virtual object does not change the diameter of the combination, but it has the maximum rating of k_i (for the combination of nodes, a virtual node is inserted in the similar way). The $W\_Average(O)$ is redefined to $W\_Average^*(O)$.

$$\begin{aligned} W\_Average^*(O) &= \frac{E+F}{|T|}. \\ E &= \sum_{o_{ki} \in O} w_{ki} * o_{ki}.rating. \\ F &= \sum_{k_j \in T/O.T} w_{kj} * O_{kj}.maxrating, \end{aligned} \tag{10}$$

where $T/O.T$ is the set of query keywords not covered by O, $O_{kj}.maxrating$ is the maximum rating of objects in O_{kj}. For example in Fig. 1, suppose the query keywords are "restaurant", "hotel" and "bar". For a combination $O = \{t_1, c_1\}$, $W\_Average(O) = w_t * t_1.rating + w_c * c_1.rating$ while $W\_Average^*(O) = w_t * t_1.rating + w_c * c_1.rating + w_s * max\_rating_s$ where w_t, w_c and w_s are the weights assigned to "bar", "restaurant" and "hotel" respectively, and max_rating_s is the highest keyword rating of objects in "hotel".

Given $O.score$ with $W\_Average^*(O)$, it is easy to prove that the property in Lemma 1 is valid. Note that the purpose of $W\_Average^*(O)$ is to apply the pruning techniques in the baseline algorithm and keyword-NNE algorithm. It does not affect the correctness of the algorithms. In addition, the property in Lemma 2 is valid no matter which of $W\_Average^*(O)$ and $W\_Average(O)$ is used in $O.score$.

8 Analysis

To help analysis, we assume a special baseline algorithm *BF-baseline* which is similar to the baseline algorithm but the best-first KRR*-tree browsing strategy is applied. For each query keyword, the child nodes of the KRR*-tree root are retrieved. The child nodes from different query keywords are combined to generate candidate keyword covers (in the same way as in the baseline algorithm, see Section 5) which are stored in a heap H. The candidate $kc \in H$ with the maximum $score$ is processed by retrieving the child nodes of kc. Then, the child nodes of kc are combined to generate more candidates which replace kc in H. This process continues until a keyword cover consisting of objects only is obtained. This keyword cover is the current best solution bkc. Any candidate $kc \in H$ is pruned if $kc.score \leq bkc.score$. The remaining candidates in H are processed in the same way. Once H is empty, the current bkc is returned to BKC query. In BF-baseline algorithm, only if a candidate keyword cover kc has $kc.score > BKC.score$, it is further processed by retrieving the child nodes of kc and combining them to generate more candidates.

8.1 Baseline

However, BF-baseline algorithm is not feasible in practice. The main reason is that BF-baseline algorithm requires to maintain H in memory. The peak size of H can be very large because of the exhaustive combination until the first current best solution bkc is obtained. To release the memory bottleneck, the depth-first browsing strategy is applied in the baseline algorithm such that the current best solution is obtained as soon as possible (see Section 5). Compared to the best-first browsing strategy which is global optimal, the depth-first browsing strategy is a kind of greedy algorithm which is local optimal. As a consequence, if a candidate keyword cover kc has $kc.score > bkc.score$, kc is further processed by retrieving the child nodes of kc and combining them to generate more candidates. Note that $bkc.score$ increases from 0 to $BKC.score$ in the baseline algorithm. Therefore, the candidate keyword covers which are further processed in the baseline algorithm can be much more than that in BF-baseline algorithm.

Given a candidate keyword cover kc, it is further processed in the same way in both the baseline algorithm and BF-baseline algorithm, i.e., retrieving the child nodes of kc and combine them to generate more candidates using

$Generate\_Candidate$ function in Algorithm 3. Since the candidate keyword covers further processed in the baseline algorithm can be much more than that in BF-baseline algorithm, the total candidate keyword covers generated in the baseline algorithm can be much more than that in BF-baseline algorithm.

Note that the analysis captures the key characters of the baseline algorithm in BKC query processing which are inherited from the methods for mCK query processing [17], [18]. The analysis is still valid if directly extending the methods [17], [18] to process BKC query as introduced in Section 4.

8.2 Keyword-NNE

In keyword-NNE algorithm, the best-first browsing strategy is applied like BF-baseline but large memory requirement is avoided. For the better explanation, we can imagine all candidate keyword covers generated in BF-baseline algorithm are grouped into independent groups. Each group is associated with one principal node (or object). That is, the candidate keyword covers fall in the same group if they have the same principal node (or object). Given a principal node N_k, let G_{Nk} be the associated group. The example in Fig. 5 shows G_{Nk} where some keyword covers such as kc_1, kc_2 have $score$ greater than $BKC.score$, denoted as G^1_{Nk}, and some keyword covers such as kc_3, kc_4 have $score$ not greater than $BKC.score$, denoted as G^2_{Nk}. In BF-baseline algorithm, G_{Nk} is maintained in H before the first current best solution is obtained, and every keyword cover in G^1_{Nk} needs to be further processed.

In keyword-NNE algorithm, the keyword cover in G_{Nk} with the highest score, i.e., $lbkc_{Nk}$, is identified and maintained in memory. That is, each principal node (or object) keeps its $lbkc$ only. The total number of principal nodes (or objects) is $\mathbf{O}(n \log n)$ where n is the number of principal objects. So, the memory requirement for maintaining H is $\mathbf{O}(n \log n)$. The (almost) linear memory requirement makes the best-first browsing strategy practical in keyword-NNE algorithm. Due to the best-first browsing strategy, $lbkc_{Nk}$ is further processed in keyword-NNE algorithm only if $lbkc_{Nk}.score > BKC.score$.

8.2.1 Instance Optimality

The instance optimality [6] corresponds to the optimality in every instance, as opposed to just the worst case or the average case. There are many algorithms that are optimal in a worst-case sense, but are not instance optimal. An example is binary search. In the worst case, binary search is guaranteed to require no more than $\log N$ probes for N data items. By linear search which scans through the sequence of data items, N probes are required in the worst case. However, binary search is not better than linear search in all instances. When the search item is in the very first position of the sequence, a positive answer can be obtained in one probe and a negative answer in two probes using linear search. The binary search may still require $\log N$ probes.

Instance optimality can be formally defined as follows: for a class of correct algorithms $\mathbf{A}$ and a class of valid input $\mathbf{D}$ to the algorithms, $cost(\mathcal{A}, \mathcal{D})$ represents the amount of a resource consumed by running algorithm $\mathcal{A} \in \mathbf{A}$ on input $\mathcal{D} \in \mathbf{D}$. An algorithm $\mathcal{B} \in \mathbf{A}$ is instance optimal over $\mathbf{A}$ and $\mathbf{D}$ if $cost(\mathcal{B}, \mathcal{D}) = \mathbf{O}(cost(\mathcal{A}, \mathcal{D}))$ for $\forall \mathcal{A} \in \mathbf{A}$ and $\forall \mathcal{D} \in \mathbf{D}$. This cost could be running time of algorithm $\mathcal{A}$ over input $\mathcal{D}$.

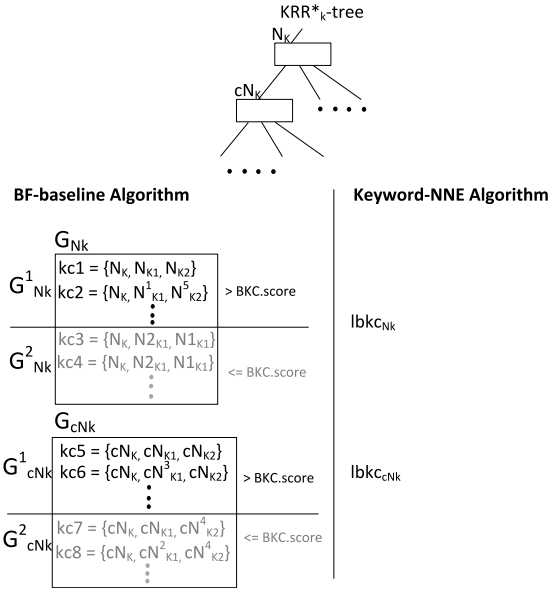


Fig. 5. BF-baseline versus keyword-NNE.

Theorem 1. *Let* $\mathbf{D}$ *be the class of all possible spatial databases where each tuple is a spatial object and is associated with a keyword. Let* $\mathbf{A}$ *be the class of any correct* BKC *processing algorithm over* $\mathcal{D} \in \mathbf{D}$*. For all algorithms in* $\mathbf{A}$*, multiple KRR*-trees, each for one keyword, are explored by combining nodes at the same hierarchical level until leaf node, and no combination of objects (or nodes of KRR*-trees) has been pre-processed, keyword-NNE algorithm is optimal in terms of the number of candidate keyword covers which are further processed.*

Proof. Due to the best-first browsing strategy, $lbkc_{Nk}$ is further processed in keyword-NNE algorithm only if $lbkc_{Nk}.score > BKC.score$. In any algorithm $\mathcal{A} \in \mathbf{A}$, a number of candidate keyword covers need to be generated and assessed since no combination of objects (or nodes of KRR*-trees) has been pre-processed. Given a node (or object) N, the candidate keyword covers generated can be organized in a group if they contain N. In this group, if one keyword cover has $score$ greater than $BKC.score$, the possibility exists that the solution of BKC query is related to this group. In this case, $\mathcal{A}$ needs to process at least one keyword cover in this group. If $\mathcal{A}$ fails to do this, it may lead to an incorrect solution. That is, no algorithm in $\mathbf{A}$ can process less candidate keyword covers than keyword-NNE algorithm. □

8.2.2 Candidate Keyword Covers Processing

Every candidate keyword cover in G^1_{Nk} is further processed in BF-baseline algorithm. In the example in Fig. 5, kc_1 is further processed, so does every $kc \in G^1_{Nk}$. Let us look closer at $kc_1 = \{N_k, N_{k1}, N_{k2}\}$ processing. As introduced in Section 4, each node N in KRR*-tree is defined as $N(x, y, r, l_x, l_y, l_r)$ which can be represented with 48 bytes. If the disk pagesize is 4,096 bytes, the reasonable fan-out of KRR*-tree is 40-50. That is, each node in kc_1 (i.e., N_k, N_{k1} and N_{k2}) has 40-50

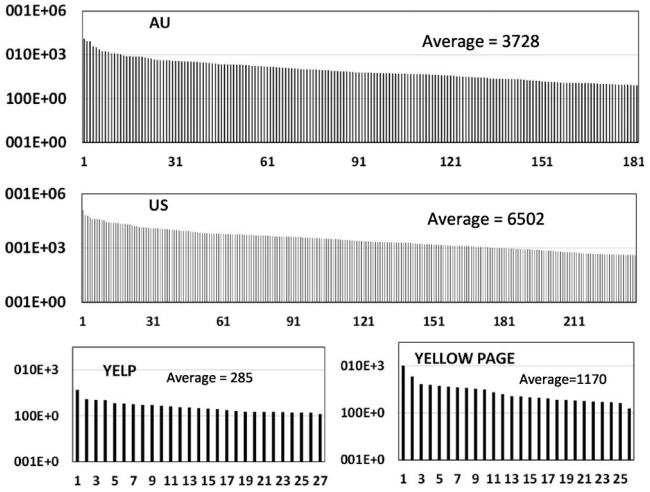
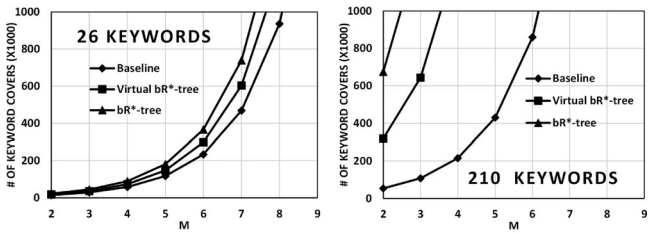


Fig. 6. The distribution of keyword size in test data sets.



(a) Yellow Page and Yelp (b) AU and US

Fig. 7. Baseline, Virtual bR*-tree and bR*-tree.

child nodes. In kc_1 processing in BF-baseline algorithm, these child nodes are combined to generate candidate keyword covers using Algorithm 3.

In keyword-NNE algorithm, one and only one keyword cover in G^1_{Nk}, i.e., $lbkc_{Nk}$, is further processed. For each child node cN_k of N_k, $lbkc_{cNk}$ is computed. For computing $lbkc_{cNk}$, a number of keyword-NNs of cN_k are retrieved and combined to generate more candidate keyword covers using Algorithm 3. The experiments on real data sets illustrate that only 2-4 keyword-NNs in average in each non-principal query keyword are retrieved in $lbkc_{cNk}$ computation.

When further processing a candidate keyword cover, keyword-NNE algorithm typically generates much less new candidate keyword covers compared to BF-baseline algorithm. Since the number of candidate keyword covers further processed in keyword-NNE algorithm is optimal (Theorem 1), the number of keyword covers generated in BF-baseline algorithm is much more than that in keyword-NNE algorithm. In turn, we conclude that the number of keyword covers generated in baseline algorithm is much more than that in keyword-NNE algorithm. This conclusion is independent of the principal query keyword since the analysis does not apply any constraint on the selection strategy of principal query keyword.

9 Experiment

In this section we experimentally evaluate keyword-NNE algorithm and the baseline algorithm. We use four real data sets, namely Yelp, Yellow Page, AU, and DE. Specifically, Yelp is a data set extracted from Yelp Academic Data Set (www.yelp.com) which contains 7,707 POIs (i.e., points of interest, which are equivalent to the objects in this work) with 27 keywords where the average, maximum and minimum number of POIs in each keyword are 285, 1,353 and 120 respectively. Yellow Page is a data set obtained from yellowpage.com.au in Sydney which contains 30,444 POIs with 26 keywords where the average, maximum and minimum number of POIs in each keyword are 1,170, 10,284 and 154 respectively. All POIS in Yelp has been rated by customers from 1 to 10. About half of the POIs in Yellow Page have been rated by Yelp, the unrated POIs are assigned average rating 5. AU and US are extracted from a public source.[2] AU contains 678,581 POIs in Australia with 187 keywords where the average, maximum and minimum number of POIs in each keyword are 3,728, 53,956 and 403 respectively. US contains 1,541,124 POIs with 237 keywords where the average, maximum and minimum number of POIs in each keyword are 6,502, 122,669 and 400. In AU and US, the keyword ratings from 1 to 10 are randomly assigned to POIs. The ratings are in normal distribution where the mean $\mu = 5$ and the standard deviation $\sigma = 1$. The distribution of POIs in keywords are illustrated in Fig. 6. For each data set, the POIs of each keyword are indexed using a KRR*-tree.

We are interested in 1) the number of candidate keyword covers generated, 2) BKC query response time, 3) the maximum memory consumed, and 4) the average number of keyword-NNs of each principal node (or object) retrieved for computing $lbkc$ and the number of $lbkc$s computed for answering BKC query. In addition, we test the performance in the situation that the weighted average of keyword ratings is applied as discussed in Section 7. All algorithms are implemented in Java 1.7.0. and all experiments have been performed on a Windows XP PC with 3.0 Ghz CPU and 3 GB main memory.

In Fig. 7, the number of keyword covers generated in baseline algorithm is compared to that in the algorithms directly extended from [17], [18] when the number of query keywords m changes from 2 to 9. It shows that the baseline algorithm has better performance in all settings. This is consistent with the analysis in Section 5. The test results on Yellow Page and Yelp data sets are shown in Fig. 7a which represents data sets with small number of keywords. The test results on AU and US data sets are shown in Fig. 7b which represents data set with large number of keywords. As observed, when the number of keywords in a data set is small, the difference between baseline algorithm and the directly extended algorithms is reduced. The reason is that the single tree index in the directly extended algorithms has more pruning power in this case (as discussed in Section 4).

9.1 Effect of m

The number of query keywords m has significant impact to query processing efficiency. In this test, m is changed from 2 to 9 when $\alpha = 0.4$. Each BKC query is generated by randomly selecting m keyword from all keywords as the query

2. http://s3.amazonaws.com/simplegeo-public/places_dump_20110628.zip.

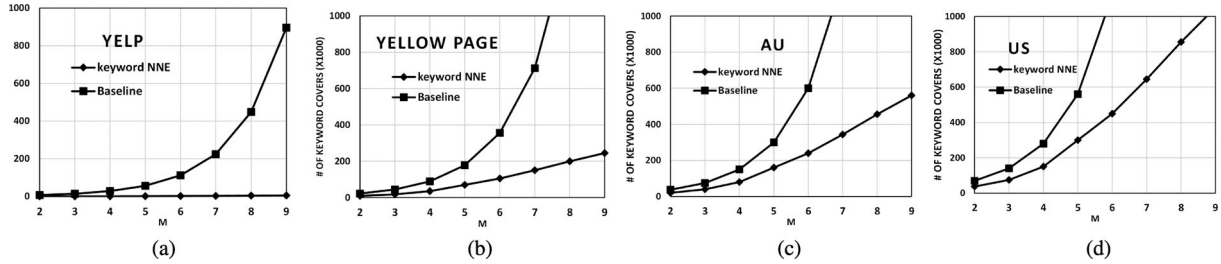


Fig. 8. Number of candidate keyword covers generated versus m ($\alpha = 0.4$).

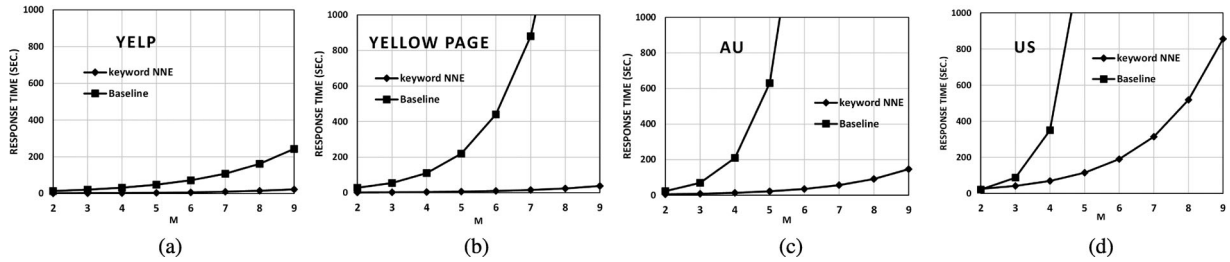


Fig. 9. Response time versus m ($\alpha = 0.4$).

keywords. For each setting, we generate and perform 100 BKC queries, and the averaged results are reported.[3] Fig. 8 shows the number of candidate keyword covers generated for BKC query processing. When m increases, the number of candidate keyword covers generated increases dramatically in the baseline algorithm. In contrast, keyword-NNE algorithm shows much better scalability. The reason has been explained in Section 8.

Fig. 9 reports the average response time of BKC query when m changes. The response time is closely related to the candidate keyword covers generated during the query processing. In the baseline algorithm, the response time increases very fast when m increases. This is consistent with the fast increase of the candidate keyword covers generated when m increases. Compared to the baseline algorithm, the keyword-NNE algorithm shows much slower increase when m increases.

For processing the BKC queries at the same settings of m and α, the performances are different on data sets US, AU, YELP and Yellow Page as shown in Figs. 8 and 9. The reason is that the average number of objects in one keyword in data sets US, AU, YELP and Yellow Page are 6,502, 3,728, 1,170 and 285 respectively as shown in Fig. 6; in turn, the average numbers of objects in one query keyword in the BKC queries on data set US, AU, YELP and Yellow Page are expected to be the same. The experimental results show the higher average number such as on data set US leads to the more candidate keyword covers and the more processing time.

9.2 Effect of α

This test shows the impact of α to the performance. As shown in Equation (2), α is an application specific parameter to balance the weight of keyword rating and the diameter in the score function. Compared to m, the impact of α to the performance is limited. When $\alpha = 1$, BKC query is degraded to mKC query where the distance between objects is the sole factor and keyword rating is ignored. When α changes from 1 to 0, more weight is assigned to keyword rating. In Fig. 10, an interesting observation is that with the decrease of α the number of keyword covers generated in both the baseline algorithm and keyword-NNE algorithm shows a constant trend of slight decrease. The reason behind is that KRR*-tree has a keyword rating dimension. Objects close to each other geographically may have very different ratings and thus they are in different nodes of KRR*-tree. If more weight is assigned to keyword ratings, KRR*-tree tends to have more pruning power by distinguishing the objects close to each other but with different keyword ratings. As a result, less candidate keyword covers are generated. Fig. 11 presents the average response time of queries which are consistent with the number of candidate keyword covers generated.

BKC query provides robust solutions to meet various practical requirements while mCK query cannot. Suppose we have three query keywords in Yelp data set, namely, "bars", "hotels and travel", and "fast food". When $\alpha = 1$, the BKC query (equivalent to mCK query) returns *Pita House*, *Scottsdale Neighborhood Trolley*, and *Schlotzskys* (the names of the selected objects in keyword "bars", "hotels and travel", and "fast food" respectively) where the lowest keyword rating is 2.5 and the maximum distance is 0.045 km. When $\alpha = 0.4$, the BKC query returns *The Attic*, *Enterprise Rent-A-Car* and *Chick-Fil-A* where the lowest keyword rating is 4.5 and the maximum distance is 0.662 km.

9.3 Maximum Memory Consumption

The maximum memory consumed by the baseline algorithm and keyword-NNE algorithm are reported in Fig. 12 (the average results of 100 BKC queries on each of four data sets). It shows that the maximum memory consumed in keyword-NNE algorithm is up to 0.5 MB in all settings of m while it increases very fast when m increases in the baseline algorithm. As discussed in Section 8, keyword-NNE algorithm only maintains the principal nodes (or objects) in

3. In this work, all experimental results are obtained in the same way.

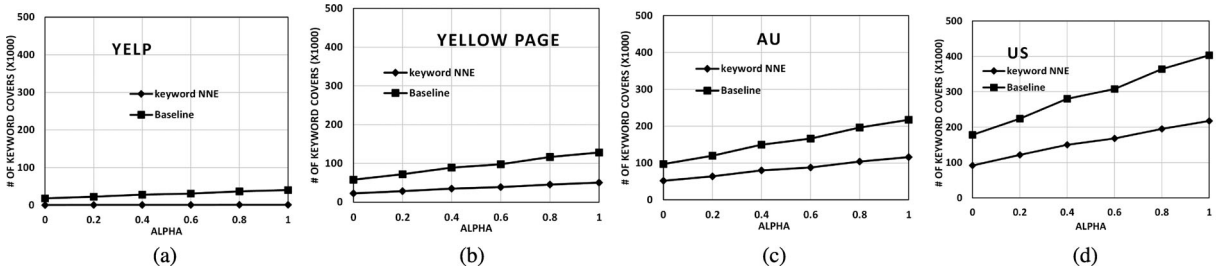


Fig. 10. Number of candidate keyword covers generated versus $\alpha(m = 4)$.

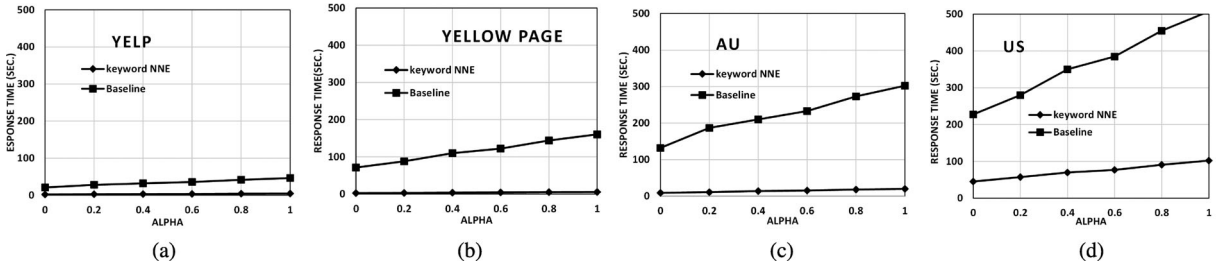


Fig. 11. Response time versus $\alpha(m = 4)$.

memory while the baseline algorithm maintains candidate keyword covers in memory.

9.4 Keyword-NNE

The high performance of keyword-NNE algorithm is due to that each principal node (or object) only retrieves a few keyword-NNs in each non-principal query keyword. Suppose all retrieved keyword-NNs in keyword-NNE algorithm are kept in a set S. In Fig. 13a, the average size of S is shown. The data sets are randomly sampled so that the number of objects in each query keyword in a BKC query is from 100 to 3,000. It illustrates that the impact of the number of objects in query keywords to the size of S is limited. On the contrary, it shows that the size of S is clearly influenced by m. When m increases from 2 to 9, S increases linearly. In average, a principal node (or object) only retrieves 2-4 keyword-NNs in each non-principal query keyword. Fig. 13b shows the number of $lbkc$s computed in query processing. We can see less than 10 percent of principal nodes (or objects) need to compute their $lbkc$s in different sizes of data sets. In other words, 90 percent of the overall principal nodes (or objects) are pruned during the query processing.

9.5 Weighted Average of Keyword Ratings

The tests compare the weighted average of keyword rating and the minimum keyword rating to performance. The average experimental results of 100 BKC queries on each of four data sets are reported in Fig. 14. We can see the difference between these two situations is trivial. This is because the score computation in the situation of the minimum keyword rating is fundamentally equivalent to that in the situation of weight average. In the former situation, if a combination O of objects (or their MBRs) does not cover a keyword, the rating of this keyword used for computing $O.score$ is 0 while it is the maximum rating of this keyword in the latter situation.

10 Conclusion

Compared to the most relevant mCK query, BKC query provides an additional dimension to support more sensible decision making. The introduced baseline algorithm is inspired by the methods for processing mCK query. The baseline algorithm generates a large number of candidate keyword covers which leads to dramatic performance drop when more query keywords are given. The proposed keyword-NNE algorithm applies a different processing strategy, i.e., searching local best solution for each object in a certain query keyword. As a consequence, the number of candidate keyword covers generated is significantly reduced. The analysis reveals that the number of candidate keyword covers which need to be further processed in

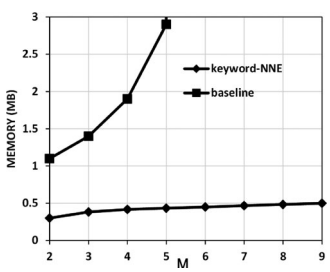
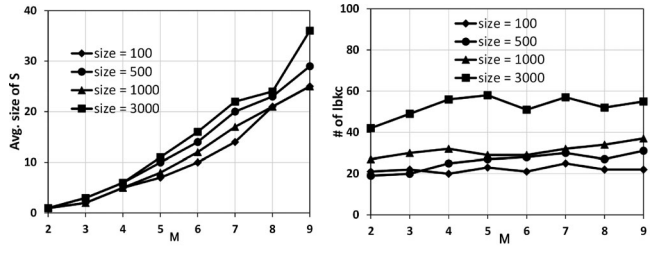
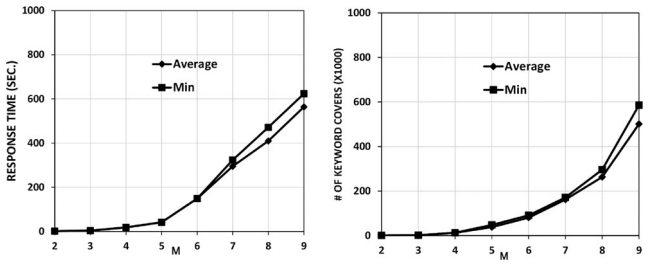


Fig. 12. Maximum memory consumed versus m ($\alpha = 0.4$).



(a) Average size of S vs. m. (b) Number of $lbkc$s computed vs. m.

Fig. 13. Features of keyword-NNE ($\alpha = 0.4$).



(a) Response time vs. m. (b) Number of nodes visited vs. m.

Fig. 14. Weighted average versus minimum ($\alpha = 0.4$).

keyword-NNE algorithm is optimal and processing each keyword candidate cover typically generates much less new candidate keyword covers in keyword-NNE algorithm than in the baseline algorithm.

ACKNOWLEDGMENTS

This research was partially supported by Natural Science Foundation of China (Grant No. 61232006), the Australian Research Council (Grants No. DP110103423 and No. DP120102829), and 863 National High-Tech Research Plan of China (No. 2012AA011001).

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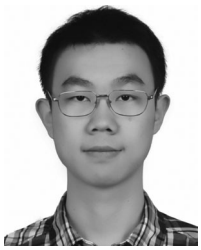

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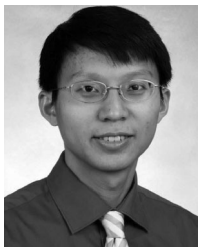

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