On Generalizing Collective Spatial Keyword Queries

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Abstract—With the proliferation of spatial-textual data such as location-based services and geo-tagged websites, spatial keyword queries are ubiquitous in real life. One example of spatial-keyword query is the so-called collective spatial keyword query (CoSKQ) which is to find for a given query consisting a query location and several query keywords a set of objects which covers the query keywords collectively and has the smallest cost wrt the query location. In the literature, many different functions were proposed for defining the cost and correspondingly, many different approaches were developed for the CoSKQ problem. In this paper, we study the CoSKQ problem systematically by proposing a unified cost function and a unified approach for the CoSKQ problem (with the unified cost function). The unified cost function includes all existing cost functions as special cases and the unified approach solves the CoSKQ problem with the unified cost function in a unified way. Experiments were conducted on both real and synthetic datasets which verified our proposed approach.

Index Terms—Spatial keyword queries, unified framework

1 INTRODUCTION

Nowadays, geo-textual data which refers to data with both spatial and textual information is ubiquitous. Some examples of geo-textual data include the spatial points of interest (POI) with textual description (e.g., restaurants, cinema, tourist attractions, and hotels), geo-tagged web objects (e.g., webpages and photos at Flickr), and also geo-social networking data (e.g., users of FourSquare have their check-in histories which are spatial and also profiles which are textual).

One application based on geo-textual data is to search a set of (geo-textual) objects wrt a query consisting of a query location (e.g., the location one is located at) and some textual information (e.g., some keywords expressing the targets one wants to search) such that the objects have their textual information matching the query keywords and their locations close to the query location. One scenario of this application is that a tourist wants to find several POIs such that s/he could do sight-seeing, shopping and dining and the POIs are close to the hotel. In this case, the user can set the query location to the hotel location and the query keywords to be “attractions”, “shopping” and “restaurant” to search for a set of POIs. Another scenario is that a manager wants to set up a project consortium of partners close to each other such that they together offer the capabilities required for successful execution of the whole project. In this case, the user can issue the query with his/her location as the query location and the required skills for the partners as the query keywords to find a group of people.

The above applications were captured by the so-called Collective Spatial Keyword Query (CoSKQ) in the literature. Let $O$ be a set of objects, where each object $o \in O$ is associated with a spatial location, denoted by $o.\lambda$, and a set of keywords, denoted by $o.\psi$. Given a query $q$ with a location $q.\lambda$ and a set of keywords $q.\psi$, the CoSKQ problem is to find a set $S$ of objects such that $S$ covers $q.\psi$, i.e., $q.\psi \subseteq \bigcup_{o \in S}o.\psi$, and the cost of $S$, denoted by $cost(S)$, is minimized.

In the literature, many different cost functions have been proposed for $cost(S)$ in the CoSKQ problem, and these cost functions are applicable in different scenarios in addition to the above examples. For the CoSKQ problem with each particular cost function, at least one approach has been designed, which we briefly review as follows.

Different cost functions. Five different cost functions have been proposed for the CoSKQ problem, namely, $cost_{Sum}$, $cost_{MaxMax}$, $cost_{MaxMax2}$, $cost_{MinMax}$, and $cost_{SumMax}$. For example, $cost_{Sum}(S)$ defines the cost to the summation of the distances from the query location to the objects in $S$, and $cost_{MaxMax}(S)$ defines the cost to a linear combination of the maximum distance between the query location and an object in $S$ and the maximum pairwise distance among the objects in $S$. The definitions of the rest of cost functions would be introduced later. Each cost function has its own semantic meaning and depending on the application scenario, an appropriate cost function is used.

Different approaches. For the CoSKQ problem with each of these existing cost functions, which was proved to be NP-hard, at least one solution (including an exact algorithm and an approximate algorithm) was developed, and these solutions usually differ from one another. For example, the exact algorithm for the CoSKQ problem with $cost_{Sum}$ is a dynamic programming algorithm, while that for the one with $cost_{MaxMax}$ is a branch-and-bound algorithm. Usually, an existing algorithm for the CoSKQ problem with a particular cost function cannot be used to solve that with another cost function.

In this paper, we study the CoSKQ problem systematically by proposing a unified cost function and a unified approach for the CoSKQ problem (with the unified cost function). Without the unified approach, we need to handle different cost functions by different algorithms, which increases the difficulty...
for CoSKQ to be used in practice. Also, when researchers work on improving the performance of an algorithm, only the corresponding cost function is benefited. Although sometimes it is possible that one algorithm originally designed for one cost function can be adapted for another cost function, the performance of the adapted algorithm is not satisfactory. A better idea is to have a unified cost function and a unified approach, where the unified cost function captures all known cost functions and some other cost functions which are not known before but useful.

Specifically, the main contribution is summarized as follows.

**A unified cost function.** We propose a unified cost function \( \text{cost}_{\text{unified}} \) which expresses all existing cost functions and a few new cost functions that have not been studied before. The core idea of \( \text{cost}_{\text{unified}} \) is that first two distance components, namely the query-object distance component and the object-object distance component, are defined, where the former is based on the distances between the query location and those of the objects and the latter is based on the pairwise distances among the set of objects and then \( \text{cost}_{\text{unified}} \) is defined based on the two distance components carefully so that all existing cost functions are captured (Note that this is possible since all ingredients of defining a cost function are distances between the query location and and those distances among objects which are captured by the two components.).

**A unified approach.** We design a unified approach, which consists of one exact algorithm and one approximate algorithm, for the CoSKQ problem with the unified cost function. For the CoSKQ problem with the cost function instantiated to those existing cost functions, which have been proved to be NP-hard, our exact algorithm is superior over the state-of-the-arts in that it not only has a unified procedure, but also runs faster under all settings for some cost functions (e.g., \( \text{cost}_{\text{MinMax}} \) and \( \text{cost}_{\text{MinMax2}} \)) and under the majority of settings for the other cost functions, and our approximate algorithm is always among those algorithms which give the best approximation ratios and runs faster than those algorithms which give similar approximation ratios. For the CoSKQ problem with the cost function instantiated to those new cost functions that have not been studied before, our exact algorithm runs reasonably fast and our approximate algorithm provides certain approximation ratios.

Besides, we conducted extensive experiments based on both real and synthetic datasets which verified our unified approach.

The rest of this paper is organized as follows. Section 2 gives the related work. Section 3 introduces the unified cost function and Section 4 presents the unified approach for CoSKQ. Section 5 gives the empirical study and Section 6 concludes the paper.

2 Related Work

Many existing studies on spatial keyword queries focus on retrieving a single object that is close to the query location and relevant to the query keywords.

A boolean \( k \)NN query [12], [3], [24], [30], [27] finds a list of \( k \) objects each covering all specified query keywords. The objects in the list are ranked based on their spatial proximity to the query location.

A top-\( k \) \( k \)NN query [8], [13], [15], [19], [20], [9], [25] adopts the ranking function considering both the spatial proximity and the textual relevance of the objects and returns top-\( k \) objects based on the ranking function. This type of queries has been studied on Euclidean space [8], [18], [15], road network databases [19], trajectory databases [20], [9] and moving object databases [25].

Usually, the methods for this kind of queries adopt an index structure called the IR-tree [8], [23] capturing both the spatial proximity and the textual information of the objects to speed up the keyword-based nearest neighbor (NN) queries and range queries. In this paper, we also adopt the IR-tree for keyword-based NN queries and range queries.

Some other studies on spatial keyword queries focus on finding an object set as a solution. Among them, some [2], [17], [2] studied the collective spatial keyword queries (CoSKQ). Cao et al. [3], [2] proposed four cost functions, namely \( \text{cost}_{\text{Sum}}, \text{cost}_{\text{MinMax}}, \text{cost}_{\text{MinMax}} \) and \( \text{cost}_{\text{MinMax2}} \), and developed algorithms for the CoSKQ problem with the first three cost functions, leaving that with the fourth cost function, i.e., \( \text{cost}_{\text{MinMax2}} \), as future work. Besides, they studied two variations of CoSKQ, namely top-\( k \) CoSKQ and weighted CoSKQ, in [2]. Long et al. [17] proposed exact and approximate algorithms for the CoSKQ problem with \( \text{cost}_{\text{MinMax2}} \) and also that with a new cost function \( \text{cost}_{\text{MinMax2}} \). The details of these cost functions are described in Section 3. In this paper, we also study the CoSKQ problem. Specifically, we propose a unified cost function which include all existing cost functions as special cases and based on the unified cost function, we design a unified approach, consisting of an exact algorithm and an approximate algorithm.

Another query that is similar to the CoSKQ problem is the \( m \)CK query [28], [29], [14] which takes a set of \( m \) keywords as input and finds \( m \) objects with the minimum diameter that cover the \( m \) keywords specified in the query. In the existing studies of \( m \)CK queries, it is usually assumed that each object contains a single keyword. There are some variants of the \( m \)CK query, including the \( SK-COVER \) [7] and the \( BRC \) query [19]. These queries are similar to the CoSKQ problem in that they also return an object set that covers the query keywords, but they only take a set of keywords as input. In contrast, the CoSKQ problem studied in this paper takes both a set of keywords and a spatial location as inputs.

Skovsgaard et al. [21] proposed a query to find top-\( k \) groups of objects with the ranking function considering the spatial proximity and textual relevance of the groups. Liu et al. proposed the clue-based spatio-textual query [16] which takes a set of keywords and a clue as inputs, and returns \( k \) objects with highest similarities against the clue.

There are also some studies [13], [22] on spatial keyword queries which find an object set in the road network, some [6] which find an object set with the scoring function considering an inherent cost in each object, some [4], [11] which find a region as a solution and some [1], [26] which find a route as a solution.

3 Unified Cost Function

Let \( O \) be a set of objects, where each object \( o \in O \) is associated with a spatial location, denoted by \( o.\lambda \), and a set of keywords, denoted by \( o.\psi \). Given two objects \( o_1 \) and \( o_2 \), we denote by \( d(o_1, o_2) \) the Euclidean distance between \( o_1.\lambda \) and \( o_2.\lambda \).

**Problem definition**. A collective spatial keyword query (CoSKQ) [3] is defined as follows.

**Problem 1 (CoSKQ [3])**. Given a query \( q \) with a location \( q.\lambda \) and a set of keywords \( q.\psi \), the CoSKQ problem is to find a set \( S \) of objects such that \( S \) covers \( q.\psi \), i.e., \( q.\psi \subseteq \bigcup_{o \in S} o.\psi \), and the cost of \( S \), denoted by \( \text{cost}(S) \), is minimized.

**Existing cost functions**. To the best of our knowledge, five cost functions have been proposed for defining \( \text{cost}(\cdot) \) in...
the CoSKQ problem, namely cost Summer, cost SumMax, cost MaxMax, cost MaxMax2, and cost MinMin. Specifically, these cost functions are defined as follows.

1) cost Summer, cost Summer(S) defines the cost to be the summation of the distances from the query location to the objects in S, i.e., cost Summer(S) = ∑φ∈S d(φ, q).

2) cost SumMax, cost SumMax(S) defines the cost to be a linear combination of the summation of distances from the query location to the objects in S and the maximum pairwise distance among the objects in S, i.e., cost SumMax(S) = α · ∑φ∈S d(φ, q) + (1 − α) · maxφ1,φ2∈S d(φ1, φ2), where α represents a real number in [0, 1].

3) cost MaxMax, cost MaxMax(S) defines the cost to be a linear combination of the maximum distance between the query location and an object in S and the maximum pairwise distance among the objects in S, i.e., cost MaxMax(S) = α · maxφ∈S d(φ, q) + (1 − α) · maxφ1,φ2∈S d(φ1, φ2), where α represents a real number in [0, 1].

4) cost MaxMax2, cost MaxMax2(S) defines the cost to be the larger one of the maximum distance between the query location and an object in S and the maximum pairwise distance among the objects in S, i.e., cost MaxMax2(S) = max{maxφ∈S d(φ, q), maxφ1,φ2∈S d(φ1, φ2)}.

5) cost MinMin, cost MinMin(S) defines the cost to be a linear combination of the minimum distance between the query location and an object in S and the maximum pairwise distance among the objects in S, i.e., cost MinMin(S) = α · minφ∈S d(φ, q) + (1 − α) · maxφ1,φ2∈S d(φ1, φ2), where α represents a real number in [0, 1].

(3) A unified cost function cost unified. In this paper, we propose a unified cost function cost unified which could be instantiated to many different cost functions including all those five existing ones. Before we give the exact definition of cost unified, we first introduce a distance component used for defining cost unified, namely the query-object distance component. It is defined based on the distances between the query location and the objects in S. Specifically, we denote it by Dq,o(φ, q) and define it as follows.

\[ D_{q,o}(φ, q) = \left\{ \begin{array}{ll} 0 & \text{if } φ \in S \\ \infty & \text{otherwise} \end{array} \right. \]

where φ ∈ {1, ∞, −∞} is a user parameter. Depending on the setting of φ, Dq,o(φ, q) corresponds to the summation, the maximum, or the minimum of the distances from the query location to the objects in S. Specifically, we denote it by Dq,o(φ, q) and define it as follows.

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where φ ∈ {1, ∞, −∞} is a user parameter. Depending on the setting of φ, Dq,o(φ, q) corresponds to the summation, the maximum, or the minimum of the distances from the query location to the objects in S. Specifically, we denote it by Dq,o(φ, q) and define it as follows.
1) (row b) $\text{cost}_{\text{Sum}}^{\text{Max}}$. The functionality of this cost function is equivalent to that of the cost function $\text{cost}_{\text{Sum}}$ (please see Appendix A for details), and thus we focus on $\text{cost}_{\text{Sum}}$ in this paper.

2) (row f) $\text{cost}_{\text{Min}}^{\text{Max}}$. It essentially captures the maximum among two distances, namely the distance between the query location $q, \lambda$ and its nearest object in $S$ and the distance between the two farthest objects in $S$. A common practice for an individual to explore the objects returned is to visit the object which is the nearest from the query location and explore the others, and thus this cost function is useful when people want to get at their first stop (i.e., the nearest object) fastly (this is captured by the query-object distance component) and explore the objects within a small region (this is captured by the farthest pairwise distance of the objects). Compared to the existing cost function $\text{cost}_{\text{Min}}^{\text{Max}}$, $\text{cost}_{\text{Min}}^{\text{Max}}$ has an advantage that it requires no parameter of $\alpha$.

3) (row h) $\text{cost}_{\text{Max}}$. It uses the maximum distance between the query location $q, \lambda$ and an object in $S$. This cost function can be used to find the feasible set with the closet farthest object among all feasible sets. This cost function is suitable for the scenarios where a user visits one object a time, starting from the query location each time, and wants the worst-case cost as small as possible.

4) (row i) $\text{cost}_{\text{Min}}$. It uses the distance between the query location $q, \lambda$ and its nearest object in $S$ only, which is of no interest in practice since it put no penalty on those objects that are far away from the query location, e.g., the whole set of objects corresponds to a trivial solution for the CoSKQ problem with $\text{cost}_{\text{Min}}$. Therefore, we ignore this instantiation of $\text{cost}_{\text{unified}}$.

(4) Intractability results. It is known that the CoSKQ problem with an existing cost function adopted is NP-hard [3, 17, 2]. That is, the CoSKQ problem is NP-hard under the parameter settings such that $\text{cost}_{\text{unified}}$ corresponds to an existing cost function. In this paper, we study the intractability of the CoSKQ problem with all possible parameter settings of $\alpha, \phi_1$ and $\phi_2$ for $\text{cost}_{\text{unified}}$. Specifically, we have the following result.

**Theorem 1 (Intractability).** The CoSKQ problem is NP-hard with all possible parameter settings of $\alpha, \phi_1$ and $\phi_2$ except for the setting of $\alpha = 1, \phi_1 \in \{\infty, -\infty\}$. □

**Proof.** See Appendix B □

(5) Existing Algorithms. For the CoSKQ problem with each of the existing cost functions, solution (including an exact algorithm and an approximate algorithm) was developed, and these solutions usually differ from one another. Specifically, we review the algorithms of some existing cost functions and solutions as follows.

1) $\text{cost}_{\text{Sum}}$. The exact algorithm for CoSKQ problem with $\text{cost}_{\text{Sum}}$ is a dynamic programming algorithm, while the approximate algorithm is a greedy algorithm transformed from that of the Weighted Set Cover problem [3, 2].

2) $\text{cost}_{\text{Sum}}^{\text{Max}}$. No solution is available in the literature for solving CoSKQ with $\text{cost}_{\text{Sum}}^{\text{Max}}$. This cost function is proposed in [2], but the corresponding solution is left for their future work.

3) $\text{cost}_{\text{Max}}^{\text{Max}}$. Several algorithms were proposed for CoSKQ problem with $\text{cost}_{\text{Max}}^{\text{Max}}$. One of the exact algorithms is a branch-and-bound algorithm [3], while another one is based on a distance owner-driven approach [17]. One of the approximate algorithms picks the nearest neighbor set [3, 2], while two other approximate algorithms search for feasible sets in an iterative manner [3, 17, 2].

Usually, an existing algorithm for the CoSKQ problem with a particular cost function cannot be used to solve that with another cost function. In the following section, we introduce out unified approach for the CoSKQ problem with the unified cost function.

4 A Unified Approach

In this section, we introduce our unified approach which consists of one exact algorithm called Unified-E (Section 4.1) and one approximate algorithm called Unified-A (Section 4.2). While the unified cost function combines existing ones, our unified approach is not one which simply combine existing approaches. In fact, both the exact algorithm and approximate algorithm proposed in this paper are clean and elegant while existing approaches have quite different structures.

Before presenting the algorithms, we first give some definitions as follows. Given a query $q$ and an object $o \in O$, we say $o$ is a relevant object if $o, \psi \cap q, \psi \neq \emptyset$. We denote $O_q$ to be the set of all relevant objects. Given a set $S$ of objects, $S$ is said to be a feasible set if $S$ covers $q, \psi$ (i.e., $q, \psi \subseteq \bigcup_{o \in S} o, \psi$). Note that the CoSKQ problem is to find a feasible set with the smallest cost.

Given a non-negative real number $r$, we denote the circle centered at $q, \lambda$ with radius $r$ by $C(q, r)$. Similarly, the circle centered at $o, \lambda$ with radius $r$ is denoted by $C(o, r)$.

Let $q$ be a query and $S$ be a feasible set. We say that an object $o \in S$ is a query-object distance contributor wrt $S$ if $d(o, q)$ contributes in $D_q,o(S)\phi_1$. Specifically, we have the following.

- In the case of $\phi_1 = 1$ where $D_q,o(S)\phi_1 = \sum_{o \in S} d(o, q)$, each object in $S$ is a query-object distance contributor wrt $S$;
- In the case of $\phi_1 = \infty$ where $D_q,o(S)\phi_1 = \max_{o \in S} d(o, q)$, only those objects in $S$ which have the maximum distance from $q$ are the query-object distance contributors wrt $S$;
- In the case of $\phi_1 = -\infty$ where $D_q,o(S)\phi_1 = \min_{o \in S} d(o, q)$, only those objects in $S$ which have the minimum distance from $q$ are the query-object distance contributors wrt $S$.

Then, we define the key query-object distance contributor wrt $S$ to the object with the greatest distance from $q$ among all query-object distance contributors wrt $S$. The concept of "key query-object distance contributor" is inspired by the concept of "query distance owner" proposed in [17], and the concept of "key query-object distance contributor" is more general in the sense that a query distance owner corresponds to a key query distance contributor in the case of $\phi_1 = \infty$ but not in other cases.

Let $S$ be a set of objects and $o_1$ and $o_2$ are two objects in $S$. We say that $o_1$ and $o_2$ are object-object distance contributors wrt $S$ if $d(o_1, o_2)$ contribute in $\max_{o, o' \in S} d(o, o')$, i.e., $(o_1, o_2) = \arg \max_{o, o' \in S} d(o, o')$.

Given a query $q$ and a keyword $t$, the $t$-keyword nearest neighbor of $q$, denoted by $NN(q, t)$, it defined to be the nearest neighbor (NN) of $q$ containing keyword $t$. Similarly, $NN(o, t)$...
is defined to be the NN of o containing keyword t. Besides, we define the nearest neighbor set of q, denoted by N(q) to be the set containing q’s t-keyword nearest neighbor for each t ∈ q, i.e., N(q) = ∪t∈q,φNN(q, t). Note that N(q) is a feasible set.

4.1 An Exact Algorithm

The idea of Unified-E is to iterate through the object-object distance contributors and search for the best feasible set S’ in each iteration. This allows CoSQK with different cost functions to be executed efficiently. Note that each existing algorithm [3], [17], [2] is designed for a specific cost function and they cannot be used to answer CoSQK with different cost functions.

Specifically, Unified-E adopts the following search strategy.

- Step 1 (Object-Object Distance Contributors Finding): Select two objects to be the object-object distance contributors wrt the set S’ to be constructed;
- Step 2 (Key Query-Object Distance Contributor Finding): Select an object to be the key query-object distance contributor wrt the set S’ to be constructed;
- Step 3 (Best Feasible Set Construction): Construct the set S’ (which has o1, oj as the object-object distance contributors and om as the key query-object distance contributor), and update the current best solution curSet with S’ if cost(S’) < curCost, where curCost is the cost of curSet;
- Step 4 (Iterative Step): Repeat Step 1 to Step 3 until all possible object-object distance contributors and key query-object distance contributors are iterated.

The above search strategy makes quite effective pruning possible at both Step 1 and Step 2.

Pruning at Step 1. The major idea is that not each relevant objects pair is necessary to be considered as a object-object distance contributor wrt S’ to be constructed. First, only the relevant objects in RS = C(q, r1) need to be considered, where r1 is the radius of the region that depends on the parameter setting, as shown in Table 2. It can be proved that if S’ contains an object o such that d(o, q) > r1, S’ cannot be the optimal solution. Second, we can maintain a lower bound dLB and an upper bound dUB of the distance between the object-object distance contributors for pruning. For example, all those relevant objects pairs (o1, oj) with d(o1, oj) > curCost (this is because in this case, all those feasible sets S’ with (o1, oj) as the object-object distance contributor have the cost larger than that of the current best solution, i.e., the best-known cost) could be pruned, i.e., curCost is used as an upper bound. Furthermore, it could be verified easily that when φ1 ∈ (1, ∞), all those relevant object pairs (o1, oj) with d(o1, oj) < maxq∈N(q) d(q, o) − min{d(o1, q), d(oj, q)} could be pruned, i.e., maxq∈N(q) d(q, o) − min{d(o1, q), d(oj, q)} is used as a lower bound. The details of dLB and dUB for different parameter settings are presented in Table 2. Specifically, we have the following lemma.

Lemma 1. Let o1 and oj be the object-object distance contributors of the set S to be constructed. For costunified with different parameter settings, d(o1, oj) can be lower bounded by dLB and upper bounded by dUB, as shown in Table 2.

Proof. Let om be the key query-object distance contributor of S. The proof of dLB is shown as follows. When φ1 ∈ (1, ∞), d(o1, oj) ≥ d(o1, om) and d(o1, oj) ≥ d(o1, om). Besides, we know that d(o1, om) + d(o1, q) ≥ d(o1, q) by triangle inequality. Similarly, we know that d(o1, oj) + d(oj, q) ≥ d(oj, q). Since S is feasible, d(o1, om) ≥ d(oj, q). Therefore, we have d(o1, oj) ≥ d(o1, q) + min{d(o1, q), d(oj, q)} ≥ d1 ≥ min{d(o1, q), d(oj, q)} = dLB. When φ1 = −∞, we have d(o1, om) + d(o1, oj) ≥ d1 because S is feasible. Also, d(o1, q) ≥ d(o1, om) and d(o1, q) ≥ d1, because om is the object closest q. Therefore, we have d(o1, oj) ≥ d1 − d(o1, q) ≥ dLB.

The proof of dUB is shown as follows. When α = 0.5, φ1 = 1 and φ2 = 1 (costSumMax), cost(S) ≥ d(o1, q) + d(oj, q) + d(o1, oj) and d(o1, q) + d(oj, q) ≥ d(o1, oj) by triangle inequality. If d(o1, oj) ≥ curCost/2, we have cost(S) ≥ 2d(o1, oj) ≥ curCost, which means S cannot contribute to a better solution and can be pruned. When φ1 = 0.5, φ1 = ∞ and φ2 = 1 (costMaxMax), cost(S) = d(o1, q) + d(oj, q) + d(o1, q) ≥ d1 since S is a feasible set. If d(o1, oj) ≥ curCost − d1, we have cost(S) ≥ curCost and thus S can be pruned. For other parameter settings, it is easy to see that if S contain an object o with d(o, q) ≥ curCost, cost(S) ≥ curCost.

Third, given a set having o1 and oj as the object-object distance contributors, we can compute the lower bound of cost of the set, denoted by cost({o1, oj}).LB, and thus we can prune all those object pairs with cost({o1, oj})LB > curCost. The details of cost({o1, oj})LB for different parameter settings are presented in Table 2. Specifically, we have the following lemma.

Lemma 2. Let o1 and oj be the object-object distance contributors of the set S to be constructed. For costunified with different parameter settings, cost(S) can be lower bounded by cost({o1, oj})LB, as shown in Table 2.

Proof. Let om be the key query-object distance contributor of S. When φ1 = 1, it is obvious that cost(S) ≥ cost({o1, oj})LB.

When φ1 = ∞, d(o1, q) ≥ max{d(o1, q), d(oj, q)}. Since S is a feasible set, d(o1, q) ≥ d1. Thus, cost(S) ≥ d(o1, q) + max{d(o1, q), d(oj, q), d1} when φ2 = 1 (costMaxMax) and cost(S) ≥ max{d(o1, q), d(o1, q), d1, d1} when φ2 = ∞ (costMinMaxMax).

When φ1 = −∞ and φ2 = 1 (costMinMax), we know that cost(S) ≥ d(o1, oj). Also we have cost(S) ≥ d(o1, oj) + d(o1, om) ≥ d(oj, q) by triangle inequality. Similarly, we have cost(S) ≥ d(o1, om) + d(oj, q) ≥ d(o1, q). Therefore, cost(S) ≥ max{d(o1, oj), d(o1, oj), d(oj, q)}

When φ1 = −∞ and φ2 = ∞ (costMinMaxMax2), we know that cost(S) ≥ d(o1, oj). Also d(o1, q) ≥ d(o1, q) − d(o1, oj) because om must be located in the region of C(o1, oj). Similarly, d(o1, q) ≥ d(o1, q) − d(o1, oj). Therefore, cost(S) ≥ max{d(o1, oj), max{d(o1, q), d(oj, q)} − d(o1, oj)}

Pruning at Step 2. Note that only the objects in C(o1, d(o1, oj)) ∩ C(oj, d(o1, oj)) need to be considered as key query-object distance contributors for constructing S’. The major idea of the pruning is that not all possible objects in the region are necessary to be considered. Specifically, we can maintain a lower bound rLB and an upper bound rUB of the distance between the key query-object distance contributors and query. For example, in the case that φ1 = 1, all those relevant objects o with d(o, q) < max{d(o, q), d(o, q)} could be safely pruned (this is because such object o can not be the key query-object distance contributor wrt S’), i.e., max{d(o, q), d(o, q)} is used as lower bound. Figure 1(a) shows the region for the objects to be considered as the key query-object distance contributor. In the
<table>
<thead>
<tr>
<th>Cost function</th>
<th>Parameter</th>
<th>$r_1$</th>
<th>$d_{LB}$</th>
<th>$d_{UB}$</th>
<th>cost(${o_i, o_j}$)$_{LB}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{cost}_\text{SumMax}$</td>
<td>0.5</td>
<td>1</td>
<td>curCost</td>
<td>$d_f - \min{d(o_i, q), d(o_j, q)}$</td>
<td>curCost/2</td>
</tr>
<tr>
<td>$\text{cost}_\text{MaxMax}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>curCost</td>
<td>$d_f - d_f$</td>
<td>$d(o_i, o_j) + \max{d(o_i, q), d(o_j, q), d_f}$</td>
</tr>
<tr>
<td>$\text{cost}_\text{MinMax}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>curCost</td>
<td>curCost</td>
<td>$\max{d(o_i, o_j), d(o_j, q), d_f}$</td>
</tr>
<tr>
<td>$\text{cost}_\text{MinMin}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>curCost</td>
<td>$d_f - d_f$</td>
<td>$\min{\text{curCost} - d(o_i, o_j), \text{curCost}}$</td>
</tr>
<tr>
<td>$\text{cost}_\text{Sum}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>curCost</td>
<td>$\text{curCost}$</td>
<td>max($d(o_i, o_j), d(o_j, q), d_f$)</td>
</tr>
</tbody>
</table>

$d_f = \max_{o \in N(q)} d(o, q)$

**TABLE 2: Lower and upper bounds used in Step 1 of Unified-E**

<table>
<thead>
<tr>
<th>Cost function</th>
<th>Parameter</th>
<th>$r_{LB}$</th>
<th>$r_{UB}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{cost}_\text{SumMax}$</td>
<td>0.5</td>
<td>1</td>
<td>max($d(o_i, q), d(o_j, q), d_f$)</td>
</tr>
<tr>
<td>$\text{cost}_\text{MaxMax}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>max($d(o_i, q), d(o_j, q), d_f$)</td>
</tr>
<tr>
<td>$\text{cost}_\text{MinMax}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>max($d(o_i, o_j), d_f$)</td>
</tr>
<tr>
<td>$\text{cost}_\text{MinMin}$</td>
<td>0.5</td>
<td>$\infty$</td>
<td>$\min{\text{curCost} - d(o_i, o_j), \min{d(o_i, q), d(o_j, q)}}$</td>
</tr>
<tr>
<td>$\text{cost}_\text{Sum}$</td>
<td>0.5</td>
<td>1</td>
<td>max($d(o_i, q), d(o_j, q), d_f$)</td>
</tr>
</tbody>
</table>

$d_f = \max_{o \in N(q)} d(o, q)$

**TABLE 3: Lower and upper bounds used in Step 2 of Unified-E**

Specifically, we have the following lemma.

**Lemma 3.** Let $o_i$ and $o_j$ be the object-object distance contributors and $o_m$ be the key query-object distance contributors of the set $S$ to be constructed. For $\text{cost}_\text{unified}$ with different parameter settings, $d(o_m, q)$ can be lower bounded by $r_{LB}$ and upper bounded by $r_{UB}$, as shown in Table 3.

**Proof.** The proof of $r_{LB}$ is shown as follows. When $\phi_1 \in \{1, \infty\}$, $d(o_m, q) > d_f$ because otherwise $S$ is not a feasible set. For $\text{cost}_\text{SumMax}, \text{cost}_\text{MaxMax}$ and $\text{cost}_\text{Sum}$, we do not need to consider an object $o$ if $d(o, q) < \min\{d(o_i, q), d(o_j, q)\}$ because it cannot be the key query-object distance contributor of $S$ by definition. Similarly, for $\text{cost}_\text{MaxMax2}$, we do not need to consider object $o$ if $d(o, q) < d(o_i, o_j)$ because it cannot be the key query-object distance contributor of $S$. When $\phi_1 = -\infty$, we set $r_{LB} = d_f - d(o_i, o_j)$ because otherwise $S$ is not a feasible set.

The proof of $r_{UB}$ is shown as follows. For $\text{cost}_\text{SumMax}$ and $\text{cost}_\text{MaxMax}$, if $S$ contains an object $o$ with $d(o, q) \geq \text{curCost} - d(o_i, o_j)$, it is obvious that $\text{cost}(S) \geq \text{curCost}$. Similarly, for $\text{cost}_\text{MaxMax2}$ ($\text{cost}_\text{Sum}$), if $S$ contains an object $o$ with $d(o, q) \geq \text{curCost} - d(o_i, o_j)$, $\text{cost}(S) \geq \text{curCost}$. For $\text{cost}_\text{MinMax}$ and $\text{cost}_\text{MinMin}$, we do not need to consider an object $o$ if $d(o, q) \geq \min\{d(o_i, q), d(o_j, q)\}$ because it cannot be the key query-object distance contributor of $S$ by definition. Also, in $\text{cost}_\text{MinMax}$, if $d(o, q) \geq \text{curCost} - d(o_i, o_j)$, $\text{cost}(S) \geq \text{curCost}$.

With the above search strategy introduced, we present the Unified-E algorithm in Algorithm 1. Specifically, we maintain an object set $\text{curSet}$ for storing the best-known solution found so far, which is initialized to $N(q)$ (line 1), and $\text{curCost}$ to be the cost of $\text{curSet}$ (line 2). Recall that $N(q)$ is a feasible set. Then, we initialize $R_S$ to be $C(q, r_1)$ (line 3) and find a set $P$ of all object pairs $(o_i, o_j)$ where $o_i$ and $o_j$ are in $R_S$ to take the roles of object-object distance contributors (line 4).

Second, we perform an iterative process as follows. Consider one iteration. We check whether the lower bound of the set containing $o_i$ and $o_j$ is larger than $\text{curCost}$ (line 6). If yes, we stop the iterations (line 7). Otherwise, we proceed to initialize the re-
Algorithm \texttt{findBestFeasibleSet}(o_i, o_j, o_m)

\textbf{Input:} Three objects \(o_i, o_j, o_m\)

\textbf{Output:} The feasible set (if any) containing \(o_i, o_j, o_m\) with the smallest cost

1. \(S' \leftarrow \emptyset\)
2. \(\psi \leftarrow q, \psi - (o_i, \omega, j, \psi, j, o_m, \psi)\)
3. If \(\psi = \emptyset\) then
   4. return \(\{o_i, o_j, o_m\}\)
5. If \(\phi_1 = -\infty\) then
   6. \(R \leftarrow C(o_i, d(o_i, o_j)) \cap C(o_j, d(o_i, o_j)) - C(o_m, d(o_m, q))\)
7. Else
   8. \(R \leftarrow C(o_i, d(o_i, o_j)) \cap C(o_j, d(o_i, o_j)) \cap C(o_m, d(o_m, q))\)
9. \(O' \leftarrow \) a set of all relevant objects in \(R\)
10. If \(O'\) does not cover \(\psi\) then
    11. return \(\emptyset\)
12. for each subset \(S''\) of \(O'\) with \(|S''| \leq |\psi|\) do
13. \(S'' \leftarrow S'' \cup \{o_i, o_j, o_m\}\)
14. if \(\text{cost}(S'') < \text{cost}(S')\) then
    15. \(S' \leftarrow S''\)
17. return \(S'\)

Algorithm 2 \texttt{findBestFeasibleSet}(o_i, o_j, o_m)

\begin{itemize}
  \item \textbf{Step 1 (Key Query-Object Distance Contributor Finding):} Select a relevant object \(o\) to be key query-object distance contributor wrt a set \(S'\) to be constructed;
  \item \textbf{Step 2 (Feasible Set Construction):} Construct the set \(S'\) (which has \(o\) as a key query-object distance contributor);
  \item \textbf{Step 3 (Optimal Set Updating):} Update the current best solution \(\text{curSet}\) if \(\text{cost}(S') < \text{curCost}\), where \(\text{curCost}\) is the cost of \(\text{curSet}\);
  \item \textbf{Step 4 (Iterative Step):} Repeat Step 1 to Step 3 until all possible key query-object distance contributors are iterated.
\end{itemize}

The above search strategy makes quite effective pruning possible at both Step 1 and Step 2.

Pruning at \textbf{Step 1}. The major idea is that not each relevant object is necessarily to be considered as a key query-object distance contributor if \(S'\) is to be constructed. Specifically, in the case of \(\phi_1 \in \{1, \infty\}\), all those relevant objects \(o\) with \(d(o, q) > \text{curCost}\) (this is because all those feasible sets \(S'\) with \(o\) as a key query-object distance contributor have the cost larger than the best-known cost \(\text{curCost}\), and thus they could be pruned) or \(d(o, q) < \max_{o \in N(q)} d(o, q) - \epsilon\) (where \(\epsilon\) is close to zero).
could be pruned. Therefore, we can maintain a region \( R \) which corresponds to the “ring region” enclosed by \( C(q, curCost) \) and \( C(q, \max_{o \in N(q)} d(o, q)) \) for pruning the search space at Step 1. In the case of \( \phi_1 = -\infty \), the region \( R \) could also be defined correspondingly. Details of the region \( R \) for different parameter settings are presented in Table 4.

**Pruning at Step 2.** We define a region \( R_o \) by the key query-object distance contributor found in Step 1 and only the objects in the region need to be considered for constructing \( S' \). The major idea of the pruning is that not all possible objects in \( R_o \) are necessary to be considered. Specifically, in the case of \( \phi_1 \in \{1, \infty\} \) all those relevant objects outside \( C(q, d(o, q)) \) could be safely pruned (this is because including one such object would fail \( o \) to be a key query-object distance contributor wrt \( S' \)). Thus, we can maintain a region \( R_o \) which corresponds to \( C(q, d(o, q)) \) for pruning the search space at Step 2. In the case of \( \phi_1 = -\infty \), the region \( R_o \) could also be maintained appropriately. Details of the region \( R_o \) for different parameter settings are presented in Table 4 as well.

With the above search strategy and pruning techniques introduced, the **Unified-A** algorithm is presented in Algorithm 3. Specifically, we maintain an object set \( curSet \) for storing the best-known solution found so far, which is initialized to \( N(q) \) (line 1) and \( curCost \) to be the cost of \( curSet \) (line 2). Then, we perform an iterative process for each relevant object \( o \in R \) in ascending order of \( d(o, q) \) (lines 3-4). Consider one iteration. First, we initialize the region \( R_o \) (line 5). Second, we invoke a procedure called \( findFeasibleSet \) (discussed later) for constructing a feasible set \( S' \) which takes \( o \) as a key query-object distance contributor wrt \( S' \) (line 6). Third, we update \( curSet \) to \( S' \) and \( curCost \) to \( cost(S') \) if \( S' \) exists and \( cost(S') < curCost \) (lines 7-9). We iterate the process with the next relevant object from \( R \) which has not been processed until all relevant objects in \( R \) have been processed.

Next, we introduce the “\( findFeasibleSet \)” procedure (used in Algorithm 3), which takes an object \( o \) and a region \( R_o \) as input and finds a feasible set \( S' \) (if any) which contains objects in \( R_o \) (including \( o \)) and has \( o \) as a key query-object distance contributor. The procedure is presented in Algorithm 4 and it is similar to the “\( findBestFeasibleSet \)” procedure (in Algorithm 2) except that it replaces the enumeration process with an iterative process (lines 8-14) for searching for a feasible set.

Depending on the value of \( \phi_1 \), the algorithm uses different criterion for picking an object at an iteration, which is described as follows.

---

**Algorithm 3** A Unified Approach (An approximate algorithm)

**Input:** A query \( q \), a set \( O \) of objects and a unified cost function \( cost_{unified}(S) = cost(S) \)

```
1: curSet ← N(q)
2: curCost ← cost(curSet)
3: Initialize the region \( R \)
4: for each relevant object \( o \in R \) in ascending order of \( d(o, q) \) do
5:  Initialize the region \( R_o \)
6:  \( S' \) ← \( findFeasibleSet(o, R_o) \)
7:  if \( S' \neq \emptyset \) and \( cost(S') < curCost \) then
8:     curSet ← \( S' \)
9:     curCost ← \( cost(S') \)
10: return curSet
```

**Algorithm 4** \( findFeasibleSet(o, R_o) \)

**Input:** An object \( o \), a region \( R_o \)

**Output:** A feasible set (if any) containing objects in \( R_o \) (including \( o \))

```
1: \( S' \) ← \{o\}
2: \( \psi \) ← \( q, \psi - o, \psi \)
3: if \( \psi = \emptyset \) then
4:     return \( S' \)
5: \( O' \) ← a set of all relevant objects in \( R_o \)
6: if \( O' \) does not cover \( \psi \) then
7:     return \( \emptyset \)
8: while \( \psi \neq \emptyset \) do
9:     if \( \phi_1 = 1 \) then
10:        \( o' \) ← arg min_{o' \in O'} d(o', o) and \( \psi \cap o'.\psi \neq \emptyset \)
11:        \( S' \) ← \( S' \cup \{o'\} \)
12:        \( \psi \) ← \( \psi - o'.\psi \)
13:     else
14:        \( o' \) ← arg min_{o' \in O'} d(o', o) and \( \psi \cap o'.\psi = \emptyset \)
15:     return \( S' \)
```

---

**Case 1:** \( \phi_1 = 1 \). It picks the object which has the smallest ratio of its distance to \( q \) to the number of relevant keywords covered. Using this criterion, the algorithm tries to pick objects in a way that minimizes the sum of the distances between the query location and the objects.

**Case 2:** \( \phi_1 \in \{-\infty, -\infty, 1\} \). It picks the object which is the nearest to \( o \) and covers some of the uncovered keywords. Using this criterion, the algorithm tries to pick objects in a way that minimizes the maximum pairwise distance between the objects.

We also develop two techniques based on the concept of information re-use for implementing the **Unified-A** with better efficiency. The details could be found in Appendix D.

**Time complexity analysis.** Let \( |R| \) be the number of relevant objects in \( R \). It could be verified that the complexity of the “\( findFeasibleSet \)” (Algorithm 3) is \( O(|\psi| \cdot |O'| \log |O'|) \) (note that a heap structure with \( |O'| \) elements could be used and there are at most \( O(|\psi|) \) operations based on the heap). Therefore, the time complexity of **Unified-A** is \( O(|R| \cdot |\psi| \cdot |O'| \log |O'|) \).

**Approximation ratio analysis.** In general, the **Unified-A** algorithm gives different approximation ratios for different parameter settings, which are given in the following theorem.

**Theorem 2.** The Unified-A algorithm gives approximation ratios as shown in Table 5 for the CoSKQ problem under different parameter settings.

**Proof.** Let \( o \) be the key query-object distance contributor wrt the optimal solution \( S_o \). Let \( S \) be the solution returned by **Unified-A**. In the following, we analyze the approximation ratio of \( cost(S)/cost(S_o) \) with different parameter settings.
The algorithm iterates each object in the region $R$, and from the way we initialize $R$, there must exist an iteration in $Unified-A$ such that it processes $o$ and thus it finds the corresponding feasible set $S'$. Note that $o$ is the key query-object distance contributor of $S'$ because the other objects in $S'$ are located in the region $R_o$. We have cost($S$) ≤ cost($S'$) because $Unified-A$ returns the feasible set with the smallest cost. The following proof shows that cost($S'$) ≤ cost($S_o$), which further implies cost($S$) ≤ γcost($S_o$), where $γ$ is the approximation ratio. We consider three cases based on the values of $φ_1$ as follows.

Case 1. $φ_1 = 1$. In this case, the approach of the algorithm to pick object to form $S'$ is modified from the approximation algorithm of the Weighted Set Cover (WSC) problem. The keywords in $ψ$ correspond to elements, the objects correspond to sets, and the distances between the objects and query correspond to the set costs. The proof is based on the approximation properties of the WSC problem. Let $w' = \sum_{o' \in S \setminus \{o\}} d(o', q) + w_o = \sum_{o' \in S \setminus \{o\}} d(o', q)$. We have $w' ≤ H_{|ψ|}w_o$ where $ψ = q, ψ - o, ψ, ψ | < |q, ψ|$ and $H_k$ is the $k$th harmonic number. There are three parameter settings (cost functions) adopt this picking object criterion, the proof are shown as follows.

Case 1(a). $α = 1, φ_1 = 1$ (cost $Sum$).

\[
\frac{\text{cost}(S' \setminus \{o\}) \setminus \{o\}}{\text{cost}(S_o \setminus \{o\})} = \frac{\sum_{o' \in S \setminus \{o\}} d(o', q) + w_o}{\sum_{o' \in S_o \setminus \{o\}} (d(o', q))} \leq \frac{d(o, q) + H_{|ψ|} w_o}{d(o, q) + w_o} \leq H_{|ψ|}
\]

Thus, the approximation ratio is not larger than $H_{|ψ|}$, where $|ψ| < |q, ψ|$, when cost $Sum$ is used.

Case 1(b). $α = 0.5, φ_1 = 1, φ_2 = 1$ (cost $Sum_{Max}$).

\[
\frac{\text{cost}(S' \setminus \{o\}) \setminus \{o\}}{\text{cost}(S_o \setminus \{o\})} = \frac{\sum_{o' \in S} (d(o, q) + \max_{o' \in S} d(o, o')) + \max_{o' \in S} d(o, o')} {\sum_{o' \in S_o} (d(o, q) + \max_{o' \in S_o} d(o, o'))} \leq \frac{2(d(o, q) + w_o)} {d(o, q) + w_o} \leq 2H_{|ψ|} \leq 2H_{|ψ|}
\]

where $(o_1, o_2) = \arg\max_{o' \in S} d(o, o')$ and $d(o_1, q) + d(o_2, q) ≤ d(o_1, q) + d(o_2, q)$ by triangle inequality.

Thus, the approximation ratio is not larger than $2H_{|ψ|}$, where $|ψ| < |q, ψ|$, when cost $Sum_{Max}$ is used.

Case 1(c). $α = 0.5, φ_1 = 1, φ_2 = ∞$ (cost $Sum_{Max2}$).

As proven in Lemma 4, cost $Sum_{Max2}$ is equivalent to cost $Sum$. Thus, the approximation bound in this case is same as that of cost $Sum$, which is $H_{|ψ|}$.

Case 2. $φ_1 = ∞$. There are three parameter settings in this case. $Unified-A$ can obtain optimal solution when $α = 1$ (i.e. cost $Max$).

Next, we discuss the case when $α = 0.5$.

The proof is modified from that of [17]. Let $α_f$ be the object in $S'$ that is farthest from $o$, $r_1 = d(o, r_1)$ and $r_2 = d(o, q)$. It could be verified that all objects in $S'$ fall in $C(o, r_1) \cap C(q, r_2)$. Besides, it could be verified that $\max_{o' \in S_o} d(o, o') = r_2$ and $\max_{o' \in S} d(o, o') ≤ r_1$, where $S_o$ is the optimal solution. Therefore, we know that cost($S_o | 0.5, ∞, φ_2$) ≥ $(r_1^{φ_1} + r_2^{φ_1})^\frac{1}{φ_1}$.

In the following, we consider two cases based on the relationship between $r_1$ and $r_2$. It could be verified that $r_1 > √2r_2$ if the diameter of $C(q, r_2)$ falls in $C(o, r_1) \cap C(q, r_2)$. Otherwise we have $r_1 ≤ √2r_2$.

Case (ii): $r_1 ≤ √2r_2$. We denote the intersection points between the boundaries of $C(o, r_1)$ and $C(q, r_2)$ by $a$ and $b$, as shown in Figure 3(a). It is observed that $max_{o' \in S} d(o, o') ≤ d(a, b)$ because all objects in $S'$ are located in $C(o, r_1) \cap C(q, r_2)$. It could be verified that $d(a, b) = 2\sqrt{r_1^2 - r_2^2/4}$. Then, cost($S'$) ≤ $r_2^{φ_2} + (2\sqrt{r_1^2 - r_2^2/4})^{φ_2}$ $\frac{1}{φ_2}$.

Let $z = \frac{r_2}{r_1}$,

\[
\frac{\text{cost}(S' \setminus \{o\}) \setminus \{o\}}{\text{cost}(S_o \setminus \{o\}) \setminus \{o\}} \leq \frac{\frac{1}{z^{φ_2}} + (2\sqrt{1 - z^2/4})^{φ_2}} {1 + \frac{1}{z^{φ_2}}} \leq \frac{1 + (z^4 - 4z^2)^{φ_2}} {1 + z^{φ_2}}
\]

When $φ_2 = 1$, we define $f(z) = \frac{1 + z\sqrt{4 - z^2}} {z^2 + 1}$ on $\{z | z \in (0, √2)\}$ because $r_1 ≤ √2r_2$. It could be verified that $f(z)$ is monotonically increasing on $(0, 0.875)$ and is monotonically decreasing on $(0.875, √2)$. Thus, $f(z) ≤ f(0.875) < 1.375$.

When $φ_2 = ∞$, we define $g(z) = \frac{\max\{1, z\sqrt{4 - z^2}\}} {\max\{1, z\}}$ on $\{z | z \in (0, √2)\}$. It could be verified that $g(z)$ is monotonically increasing on $(0, 1)$ and is monotonically decreasing on $(1, √2)$. Thus, $g(z) ≤ g(1) = \frac{1}{√3}$.

Case (ii): $r_1 > √2r_2$. Let $diam = 2r_2$ be the diameter of $C(q, r_2)$ and falls in $C(o, r_1) \cap C(q, r_2)$, as shown in Figure 3(b). Similar to case 1, it could be verified that $\max_{o' \in S} d(o, o') ≤ diam = 2r_2$. Therefore,

\[
\frac{\text{cost}(S' \setminus \{o\}) \setminus \{o\}}{\text{cost}(S_o \setminus \{o\}) \setminus \{o\}} \leq \left\{ \frac{r_2^{φ_2} + (2r_2^{φ_2})}{r_2^{φ_2} + r_2^{φ_2}} \right\}^\frac{1}{φ_2} \leq \left\{ \frac{1^{φ_2} + 2^{φ_2}} {√2^{φ_1} + 1^{φ_1}} \right\}^\frac{1}{φ_1}
\]

It could be verified that $\frac{1^{φ_2}} {2^{φ_2}} ≤ 1.25$ when $φ_2 = 1$. When $φ_2 = ∞$, we have $\frac{1^{φ_2}} {2^{φ_2}} ≤ \frac{1} {√2}$. Based on the above analysis, we can obtain the approximation bounds of the two sub-cases as follows.

<table>
<thead>
<tr>
<th>Cost Function</th>
<th>Parameter</th>
<th>$R$</th>
<th>$R_o$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$cost_{SumMax}$</td>
<td>0.5</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$cost_{Max}$</td>
<td>0.5</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$cost_{Max2}$</td>
<td>0.5</td>
<td>$∞$</td>
<td>1</td>
</tr>
<tr>
<td>$cost_{MinMax}$</td>
<td>0.5</td>
<td>$∞$</td>
<td>1</td>
</tr>
<tr>
<td>$cost_{Sum}$</td>
<td>0.5</td>
<td>$∞$</td>
<td>1</td>
</tr>
</tbody>
</table>

$\phi_1 = \max_{o \in N(q)} (d(o, q))$
<table>
<thead>
<tr>
<th>Cost function</th>
<th>Parameter</th>
<th>Unified-A</th>
<th>Best known approx. ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{cost}_{\text{MinMax}})</td>
<td>0.5 (\alpha) -\infty 1</td>
<td>2</td>
<td>3 [2]</td>
</tr>
<tr>
<td>(\text{cost}_{\text{MinMax2}})</td>
<td>0.5 (\alpha) -\infty 2</td>
<td>N.A.</td>
<td></td>
</tr>
<tr>
<td>(\text{cost}_{\text{Sum}})</td>
<td>1 -1</td>
<td>(H_{(\phi)})</td>
<td>N.A.</td>
</tr>
<tr>
<td>(\text{cost}_{\text{SumMax}})</td>
<td>0.5 1 (2H_{(\phi)})</td>
<td>N.A.</td>
<td></td>
</tr>
<tr>
<td>(\text{cost}_{\text{SumMax2}})</td>
<td>0.5 1 (H_{(\phi)})</td>
<td>N.A.</td>
<td></td>
</tr>
<tr>
<td>(\text{cost}_{\text{MaxMax}})</td>
<td>0.5 (\alpha) -\infty 1.375</td>
<td>1.375</td>
<td>1.375 [2]</td>
</tr>
<tr>
<td>(\text{cost}_{\text{MaxMax2}})</td>
<td>0.5 (\alpha) (\sqrt 3) (\sqrt 3)</td>
<td>[2]</td>
<td></td>
</tr>
<tr>
<td>(\text{cost}_{\text{Max}})</td>
<td>1 -\infty 1</td>
<td>N.A.</td>
<td></td>
</tr>
<tr>
<td>(\text{cost}_{\text{Min}})</td>
<td>1 -\infty 1</td>
<td>N.A.</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE 5:** Approx. ratios of Unified-A and existing solutions

**Case 2(a).** \(\alpha = 0.5, \phi_1 = \infty, \phi_2 = 1\) \((\text{cost}_{\text{MaxMax}})\).

The approximation ratio of the algorithm is not larger than \(\max\{1.375, 1.25\} = 1.375\).

**Case 2(b).** \(\alpha = 0.5, \phi_1 = \infty, \phi_2 = \infty\) \((\text{cost}_{\text{MaxMax2}})\).

The approximation ratio of the algorithm is not larger than \(\max\{\sqrt 3, \sqrt 2\} = \sqrt 3\).

**Case 3.** \(\phi_1 = -\infty\). There are three parameter settings in this case. Unified-A can obtain optimal solution when \(\alpha = 1\) (i.e. \(\text{cost}_{\text{Min}}\)). In the following, we discuss the case when \(\alpha = 0.5\).

Let \(o_j\) be the object in \(S'\) that is farthest from \(o, r_1 = d(o_j, o)\) and \(r_2 = d(o, q)\), as shown in Figure 3(c). Besides, it could be verified that \(\max_{o',o'' \in S_o} d(o, o') \geq 1\), where \(S_o\) is the optimal solution. Thus, we have

\[
\frac{\text{cost}(S'(0.5, -\infty, \phi_2))}{\text{cost}(S_o(0.5, -\infty, \phi_2))} = \left(\frac{r_2}{r_1}\right)^{2\phi_2} \leq \left(\frac{r_2}{r_1}\right)^{\phi_2} + \left(\frac{r_2}{r_1}\right)^{\phi_1} \leq 2.
\]

The approximation bounds of the two sub-cases are shown as follows.

**Case 3(a).** \(\alpha = 0.5, \phi_1 = -\infty, \phi_2 = 1\) \((\text{cost}_{\text{MinMax}})\).

**Case 3(b).** \(\alpha = 0.5, \phi_1 = -\infty, \phi_2 = \infty\) \((\text{cost}_{\text{MinMax2}})\).

We consider the following 3 sub-cases.

**Case (i):** \(r_2 \geq 2r_1\)

\[
\frac{\text{cost}(S'(0.5, -\infty, \infty))}{\text{cost}(S_o(0.5, -\infty, \infty))} \leq \frac{r_2}{r_1} \leq 1,
\]

**Case (ii):** \(r_2 \geq r_1 > \frac{r_2}{r_1}\)

\[
\frac{\text{cost}(S'(0.5, -\infty, -\infty))}{\text{cost}(S_o(0.5, -\infty, -\infty))} \leq \frac{2r_1}{r_1} \leq 2.
\]

**Case (iii):** \(r_1 \geq r_2 \geq r_1 > \frac{r_1}{r_2}\)

\[
\frac{\text{cost}(S'(0.5, -\infty, -\infty))}{\text{cost}(S_o(0.5, -\infty, -\infty))} \leq \frac{2r_1}{r_1} \leq 2.
\]

Thus, the approximation ratio is not larger than 2.

**5 EMPIRICAL STUDIES**

**5.1 Experimental Set-up**

**Datasets.** Following the existing studies [3], [17], [2], we used three real datasets in our experiments, namely Hotel, GN and Web. Dataset Hotel contains a set of hotels in the U.S. (www.allstays.com), each of which has a spatial location and a set of words that describe the hotel (e.g., restaurant, pool). Dataset GN was collected from the U.S. Board on Geographic Names (geonames.usgs.gov), where each object has a location and also a set of descriptive keywords (e.g., a geographic name such as valley). Dataset Web was generated by merging two real datasets. One is a spatial dataset called TigerCensusBlock [3] which contains a set of census blocks in Iowa, Kansas, Missouri and Nebraska. The other is WEBSPAM-UK2007 [4] which consists of a set of web documents. Table 5 shows the statistics of the three datasets.

**Query Generation.** Let \(O\) be a dataset of objects. Given an integer \(k\), we generate a query \(q\) with \(k\) query keywords similarly as [3], [17] did. Specifically, to generate \(q, \lambda\), we randomly pick a location from the MBR of the objects in \(O\), and to generate \(q, \psi\), we first rank all the keywords that are associated with objects in \(O\) in descending order of their frequencies and then randomly pick \(k\) keywords in the percentile range of \([10, 40]\).

**Cost functions.** We study all instantiations of our unified cost function except for \(\text{cost}_{\text{Min}}\) and \(\text{cost}_{\text{SumMax2}}\) since as we mentioned in Section 3 the former is of no interest and the latter is equivalent to \(\text{cost}_{\text{Sum}}\). That is, we study 7 cost functions in total, namely \(\text{cost}_{\text{MinMax}}, \text{cost}_{\text{MinMax2}}, \text{cost}_{\text{Sum}}, \text{cost}_{\text{SumMax}}, \text{cost}_{\text{SumMax2}}, \text{cost}_{\text{MaxMax}}\) and \(\text{cost}_{\text{MaxMax2}}\).

**Algorithms.** Both the Unified-E algorithm and the Unified-A algorithm are studied. For comparison, for the CoSKQ problem with an existing cost function, the state-of-the-art algorithms are used and for the CoSKQ problem with a new cost function, some adaptations of existing algorithms are used. The state-of-the-art algorithms are presented in Table 7 where Cao-E1, Cao-E2, Cao-A1, Cao-A2 and Cao-A3 refer to the algorithms MAXMAX-Exact, SUM-Exact, MAXMAX-Approx1, MAXMAX-Approx2 and SUM-Approx, respectively, and Long-E and Long-A refer to the algorithms MaxMax-Exact and SumMax-Approx, respectively. Note that though the cost function \(\text{cost}_{\text{SumMax}}\) was proposed in [2], it was left as future work to develop solutions and thus we adapt some existing algorithms for the CoSKQ problem with this cost function.

All experiments were conducted on a Linux platform with a 2.66GHz machine and 32GB RAM. The IR-tree index structure is memory resident.

---


<table>
<thead>
<tr>
<th>Cost function</th>
<th>Exact Algorithm</th>
<th>Appro. Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{cost}_{\text{MinMax2}})</td>
<td>Cao-E1 [2]*</td>
<td>Cao-A1 [2]*</td>
</tr>
<tr>
<td>(\text{cost}_{\text{SumMax}})</td>
<td>Cao-E1 [2]*</td>
<td>Cao-A3 [2]*</td>
</tr>
</tbody>
</table>

**TABLE 7:** Algorithms for comparison (those with the asterisk symbol are adaptations)

---

**TABLE 6:** Datasets used in the experiments

<table>
<thead>
<tr>
<th></th>
<th>Hotel</th>
<th>GN</th>
<th>Web</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of objects</td>
<td>20,790</td>
<td>1,868,821</td>
<td>579,727</td>
</tr>
<tr>
<td>Number of unique words</td>
<td>602</td>
<td>222,409</td>
<td>2,899,175</td>
</tr>
<tr>
<td>Number of words</td>
<td>80,645</td>
<td>18,374,228</td>
<td>249,132,883</td>
</tr>
</tbody>
</table>
5.2 Experimental Results

Following the existing studies [3, 17], [2], we used the running time and the approximation ratio (for approximate algorithms only) as measurements. Note that different sets of objects with the same costs are treated equally, and thus precision or recall are not used as measures in our experiments. For each experimental setting, we generated 500 queries and ran the algorithms with each of these queries. The average, minimum, and maximum approximation ratios were recorded and shown with bar charts.

5.2.1 Effect of \(|q, \psi|\)

Following the existing studies [3, 17], we vary the number of query keywords (i.e., \(|q, \psi|\)) from \{3, 6, 9, 12, 15\}. The results on the dataset Hotel are presented and those on the datasets GN and Web are similar and could be found in Appendix B.

1. **cost\(_{\text{MinMax}}\).** The results for cost\(_{\text{MinMax}}\) on the dataset Hotel are shown in Figure 4. According to Figure 4(a), the running time of each algorithm increases when \(|q, \psi|\) increases. Our exact algorithm Unified-E runs consistently faster than the state-of-the-art algorithm Cao-E1 and the gap becomes larger when \(|q, \psi|\) increases. This could be explained by the fact Cao-E1 performs the expensive exhaustive search on the pivot objects whose number increases fast with \(|q, \psi|\) while Unified-E only need to search on the regions that are possible to contain the object sets. Besides, our approximate algorithm Unified-A runs quite fast, e.g., less than 0.1 seconds, though it is slower than Cao-A1. According to Figure 4(b), Unified-A has its approximation ratios consistently better than Cao-A1, e.g., the largest approximation ratios of Unified-A is at most 1.569 while the largest approximation ratios of Cao-A1 is at least 1.845 (and up to 2.317). Note that there could be an significant difference between a solution with 1.569 approximation ratio and that with 2.317 approximation ratio, though it does not seem to look so, e.g., in the case an optimal solution has its cost of 10km, a 1.569-approximate solution has a cost about 16km and a 2.317-approximate solution about 23km, then the difference is about 7km (23km - 16km) which is more than half of the optimal cost. The reason could be that Unified-A performs an iterative process on the key query-object distance contributor which helps improve the approximation ratio while Cao-A1 does not. Besides, we note that the approximation ratio of Unified-A is exactly 1 for more than 90% queries, while that of Cao-A1 is less than 70%.

2. **cost\(_{\text{MinMax2}}\).** The results for cost\(_{\text{MinMax2}}\) on the dataset Hotel are shown in Figure 5, which are similar to those for cost\(_{\text{MinMax}}\), i.e., Unified-E runs consistently faster than Cao-E1 and Unified-A gives better approximation ratios than Cao-A1 with reasonable efficiency.

3. **cost\(_{\text{Sum}}\).** The results for cost\(_{\text{Sum}}\) on the dataset Hotel are shown in Figure 6. According to Figure 6(a), Unified-E runs similarly fast as Cao-E2 when \(|q, \psi| \leq 9\) and runs faster than Cao-E2 when \(|q, \psi| > 9\). Unified-E has a very restrict search space, e.g., only those dominant objects, and Cao-E2 is a dynamic programming algorithm which might be more sensitive to \(|q, \psi|\). Besides, Unified-A has a very similar running time as Cao-A3. According to Figure 6(b), Unified-A and Cao-A3 give very similar approximation ratios.

4. **cost\(_{\text{SumMax}}\).** The results for cost\(_{\text{SumMax}}\) on the dataset Hotel are shown in Figure 7, which are similar to those for cost\(_{\text{Sum}}\) except that the competitor is Cao-E1, i.e., Unified-E runs faster than Cao-E1 when \(|q, \psi|\) grows and Unified-A has similar running time and also approximation ratios as Cao-A3.

5. **cost\(_{\text{MaxMax}}\).** The results for cost\(_{\text{MaxMax}}\) on the dataset Hotel are shown in Figure 8. According to Figure 8(a), each algorithm has its running time grows when \(|q, \psi|\) increases (in particular, Cao-E1 has its running time grows the fastest). Besides, Unified-E runs consistently faster than Long-E and runs faster than Cao-E1 as well when \(|q, \psi|\) gets larger. According to Figure 8(b), all approximate algorithms including Unified-A run fast, e.g., less than 0.1 seconds, and according to Figure 8(c), Unified-A is one of two algorithms that give the best approximation ratio (the other is Long-A). Note that Unified-A runs consistently faster than Long-A, and the reason could be that Unified-A has computation strategies based on information re-use while Long-A does not. The largest approximation ratios of Unified-A is only 1.031, while that of Cao-A1 and Cao-A2 could be up to 1.904 and 1.377, respectively. Besides, Unified-A gives approximation ratio of exactly 1 for 98% queries, while that of Cao-A1 and Cao-A2 are 51% and 83%, respectively.

6. **cost\(_{\text{MaxMax2}}\).** The results for cost\(_{\text{MaxMax2}}\) on the dataset Hotel are shown in Figure 9, which are similar as those for cost\(_{\text{MaxMax}}\), i.e., Unified-E has the best efficiency in general.
Fig. 8: Effect of $[q, \psi]$ on $\text{cost}_{\text{MaxMax}}$ (Hotel) and $\text{Unified-A}$ is among one of the two algorithms which give the best approximation ratios and also run reasonably fast. Note that the largest approximation ratios of $\text{Unified-A}$ is only 1.080, while that of $\text{Cao-A1}$ and $\text{Cao-A2}$ could be up to 1.778 and 1.347, respectively.

Fig. 9: Effect of $[q, \psi]$ on $\text{cost}_{\text{MaxMax}}$ (Hotel) and $\text{Unified-A}$ is among one of the two algorithms which give the best approximation ratios and also run reasonably fast. Note that the largest approximation ratios of $\text{Unified-A}$ is only 1.080, while that of $\text{Cao-A1}$ and $\text{Cao-A2}$ could be up to 1.778 and 1.347, respectively.

5.2.2 Effect of average $|o, \psi|$

We further generated 5 datasets based on the Hotel dataset, where the average number of keywords an object contains (i.e., average $|o, \psi|$) is close to 8, 16, 24, 32, and 40, respectively. In the Hotel dataset, the average number of keywords an object contains is close to 4. To generate a dataset with its average $|o, \psi|$ equal to 8, we do the following. For each object $o$ in the Hotel dataset, we augment $o, \psi$ by including all those keywords in $o', \psi$ to $o, \psi$ (i.e., $o, \psi \leftarrow o, \psi \cup o', \psi$) where $o'$ is a randomly picked object. To generate the datasets with the average $|o, \psi|$ equal to 16, 24, 32 and 40, we repeat the above process appropriate times. We vary average $|o, \psi|$ from $\{4, 8, 16, 24, 32, 40\}$ and following (2), we use the default setting of $|q, \psi| = 10$.

1) $\text{cost}_{\text{MinMax}}$. The results for $\text{cost}_{\text{MinMax}}$ are shown in Figure 10, where the results of running time of $\text{Cao-E1}$ for $|o, \psi| \geq 24$ are not shown simply because it ran for more than 10 hours (this applies for all the following results). According to Figure 10(a), all algorithms except for $\text{Cao-E1}$ are quite scalable when $|o, \psi|$ grows. The poor scalability of $\text{Cao-E1}$ could be due to the fact that $\text{Cao-E1}$ is based on the search space of relevant objects around the candidate objects, which grows rapidly when $|o, \psi|$ increases. Besides, our exact algorithm $\text{Unified-E}$ runs consistently better than $\text{Cao-E1}$ and $\text{Unified-A}$ runs fast, though not as fast as $\text{Cao-A1}$, and gives obviously better approximation ratios than $\text{Cao-A1}$ (Figure 10(b)). Specifically, the largest approximation ratios of $\text{Unified-A}$ is only 1.454, which is small, while that of $\text{Cao-A1}$ is up to 2.536, which is not suitable for practical use.
ran for more than 1 day when \(|o,\psi| \geq 8\). Thus, for better comparison among the algorithms, we particularly use the setting of \(|q,\psi| = 8\) for \(\text{cost}_{\text{SumMax}}\). According to Figure 13(a), \(\text{Unified-E}\) runs consistently faster than \(\text{Cao-E1}\) and \(\text{Unified-A}\) runs fast, though not as fast as \(\text{Cao-A3}\), and gives a better approximation ratio (Figure 13(b)). Specifically, the largest approximation ratios of \(\text{Unified-A}\) and \(\text{Cao-A3}\) are 1.160 and 1.251, respectively.

(5) \(\text{cost}_{\text{MaxMax}}\). The results for \(\text{cost}_{\text{MaxMax}}\) are shown in Figure 14. According to Figure 14(a), \(\text{Unified-E}\) is one of the two algorithms that run the fastest and the other is \(\text{Cao-E1}\). According to Figure 14(b) and (c), all approximate algorithms including \(\text{Unified-A}\) run reasonably fast and \(\text{Unified-A}\) is one of the two algorithms which give the best approximation ratios (the other is \(\text{Long-A}\)). Specifically, the largest approximation ratios of \(\text{Unified-A}\) is only 1.135, while that of \(\text{Cao-A1}\) and \(\text{Cao-A2}\) are 2.506 and 1.534, respectively, which are much larger.

(6) \(\text{cost}_{\text{MaxMax2}}\). The results for \(\text{cost}_{\text{MaxMax2}}\) are shown in Figure 15 which are similar to those for \(\text{cost}_{\text{MaxMax}}\); i.e., \(\text{Unified-E}\) is one of the two fastest exact algorithm and \(\text{Unified-A}\) runs reasonably fast and is one of the two algorithms which give the best approximation ratios.

(7) \(\text{cost}_{\text{Max}}\). The results for \(\text{cost}_{\text{Max}}\) are shown in Figure 16(b). According to the results, both \(\text{Unified-E}\) and \(\text{Unified-A}\) run very fast, e.g., they ran less than 0.02 ms on all settings of \(|q,\psi|\).

5.2.3 Scalability Test

Following the existing studies [3, 17, 2], we generated 5 synthetic datasets for the experiments of scalability test, in which the numbers of objects used are 2M, 4M, 6M, 8M and 10M. Specifically, we generated a synthetic dataset by augmenting the GN datasets with additional objects as follows. Each time, we create a new object \(o\) with \(o,\lambda\) set to be a random location from the original GN dataset by following the distribution and \(o,\psi\) set to be a random document from GN and then add it into the GN dataset. We vary the number of objects from \(\{2M, 4M, 6M, 8M, 10M\}\), following [2], we use the default setting of \(|q,\psi| = 10\).

(1) \(\text{cost}_{\text{MinMax}}\). The results for \(\text{cost}_{\text{MinMax}}\) are shown in Figure 17. According to Figure 17(a), our exact algorithm \(\text{Unified-E}\) runs consistently faster than \(\text{Cao-E1}\) and it is scalable wrt the number of objects, e.g., it ran within 30 seconds on a dataset with 10M objects. Besides, our approximate algorithm \(\text{Unified-A}\) is also scalable, e.g., it ran within 1 second on a dataset with 10M objects, and gives near-to-optimal approximation ratios (Figure 17(b)). The largest approximation ratios of \(\text{Unified-A}\) is only 1.622, which is very small, while that of \(\text{Cao-A1}\) is 2.692, which is not practical. This also conform with our theoretical analysis that \(\text{Unified-A}\) has a better approximation ratio than \(\text{Cao-A1}\) in \(\text{cost}_{\text{MinMax}}\).

The results for the remaining cost functions are put in Appendix F due to the page limit. According to the results, we know that both \(\text{Unified-E}\) and \(\text{Unified-A}\) are scalable to large datasets.
5.3 Summary Of Experimental Results

Our exact algorithm \textit{Unified-E} is clearly the best exact algorithm for CoSKQ queries not only because it is a \textit{unified} approach but also it is always among those with the best running times (e.g., it beats the state-of-the arts \textit{consistently} for cost_{MinMax} and cost_{MinMax2}, when \(|q, \psi|\) becomes large for cost_{Sum} and cost_{SUMMax}, and under the majority of settings for cost_{MaxMax} and cost_{MaxMax2}).

Our approximate algorithm \textit{Unified-A} runs reasonably fast (e.g., for the majority settings of \(|q, \psi|\), it ran within 0.1 seconds), while sometimes it is not as fast as the competitors because \textit{Unified-A} has some more checking so that it can take care all cost functions. Meanwhile, \textit{Unified-A} is always among the those which give the best approximation ratios close to 1 and runs always faster than those algorithms which give similar approximation ratios as \textit{Unified-A}.

6 Conclusion

In this paper, we proposed a unified cost function for CoSKQ. This cost function expresses all existing cost functions in the literature and a few cost functions that have not been studied before. We designed a unified approach, which consists of one exact algorithm and one approximate algorithm. The exact algorithm runs comparably fast as the existing exact algorithms, while the approximate algorithm provides a comparable approximation ratio as the existing approximate algorithms. Extensive experiments were conducted which verified our theoretical findings.

There are several interesting future research directions. One direction is to design a cost function such that it penalizes those objects with too much keywords for fairness. Another direction is to extend CoSKQ with the unified cost function to other distance metrics such as road networks. It is also interesting to extend the unified approach to handle the route-oriented spatial keyword queries. Besides, it is left as a remaining issue to study the CoSKQ problem with a moving query point.

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References


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APPENDIX A

EQUIVALENCE OF \(\text{cost}_{\text{SumMax2}}\) AND \(\text{cost}_{\text{Sum}}\)

We have the following lemma to show the functionality of \(\text{cost}_{\text{SumMax2}}\) and \(\text{cost}_{\text{Sum}}\) are equivalent.

**Lemma 4.** Let \(S\) be an object set. \(\text{cost}_{\text{SumMax2}}(S) = \text{cost}_{\text{Sum}}(S)\).

**Proof.** Let \((o_1, o_2) = \arg \max_{o_1, o_2 \in S} d(o_1, o_2)\). We have

\[
\text{cost}_{\text{SumMax2}}(S) = \max \{ \sum_{o \in S} d(o, q), \text{cost}_{\text{Sum}}(o_1, o_2) \}.
\]

Note that \(d(o_1, q) + d(o_2, q) \geq d(o_1, o_2)\) by triangle inequality and \(\sum_{o \in S} d(o, q) \geq d(o_1, q) + d(o_2, q)\). Thus, \(\text{cost}_{\text{SumMax2}}(S) = \sum_{o \in S} d(o, q) = \text{cost}_{\text{Sum}}(S)\).

This lemma suggests that it is sufficient to consider one of these two cost functions. In this paper, we focus on the discussion on \(\text{cost}_{\text{Sum}}\).

APPENDIX B

PROOF OF THEOREM 1

We first give the decision problem of CoSKQ. Given a set \(O\) of spatial objects each \(o \in O\) associated with a location \(o.\lambda\) and a set of keywords \(o.\psi\), a query \(q.\psi\) consists of a query location \(q.\lambda\) and a set of query keywords \(q.\psi\), and a real number \(C\), the problem is to determine whether there exists a set \(S\) of objects in \(O\) such that \(S\) covers the query keywords and \(\text{cost}_{\text{unified}}(S)\) is at most \(C\).

We then prove by transforming the 3-satisfiability (3-SAT) problem which is known to be NP-Complete to the CoSKQ problem and showing the equivalence between two problems. The description of the 3-SAT problem is given as follows. Let \(U\) be a set of literals \(\{e_1, \overline{e}_1, ..., e_n, \overline{e}_n\}\) where \(\overline{e}\) is the negation of \(e\). Given an expression \(E = C_1 \land C_2 \land ... \land C_m\) where \(C_j = e_j \lor \overline{e}_j \lor \overline{e}_j\) and \(x_j, y_j, z_j \in U\) for \(1 \leq j \leq m\), the problem is to determine whether there exists a truth assignment for \(e_i\) for \(1 \leq i \leq n\) such that \(E\) is true.

Based on the value of parameter \(\phi\), we use different transformations.

**Case 1.** \(\phi = 1\). We construct a set \(O\) of 2\(n\) objects as follows. For each literal \(e_i\) in \(U\), we create an object \(o_i\) in \(O\), and for each literal \(\overline{e_i}\) in \(U\), we create an object \(o_i\) in \(O\). In total, there are \(2n\) objects in \(O\). We set the locations of the objects in \(O\) such that they are all located at the same place i.e., for any \(o \in O\), \(o.\lambda\) is identical. Besides, for each object \(o_i\) \((1 \leq i \leq n)\), we set \(o_i.\psi\) such that \(o_i.\psi\) includes a keyword \(k_i\) corresponding to \(e_i\) and a keyword \(k'_i\) corresponding to \(\overline{e}_i\). Similarly, for each object \(o_i\) \((1 \leq i \leq n)\), we set \(o_i.\psi\) such that \(o_i.\psi\) includes the keyword \(k_i\) and all \(k'_j\)’s with \(C_j\) involving \(\overline{e}_i\) for \(1 \leq j \leq m\). We construct a query \(q\) by setting \(q.\lambda\) arbitrarily and \(q.\psi\) to be a set of \(m + n\) keywords, \(\{k_1, k_2, ..., k_n, k'_1, k'_2, ..., k'_m\}\). The above transformation process could be done in polynomial time. We consider the following sub-cases for setting \(C\).

**Case 2(a).** \(\phi = 1\). We set \(C = 3 - \epsilon\) where \(\epsilon\) is close to zero.

**Case 2(b).** \(\phi = \infty\). We set \(C = 2 - \epsilon\) where \(\epsilon\) is close to zero.

We show the equivalence between two problem instances as follows. Suppose that the answer of the 3-SAT problem is “yes”, i.e., there exists a truth assignment for the literals in \(U\) such that \(E\) is correct. We denote the truth assignment by a set \(T\) of literals which are true under the assignment. Note that \(T\) has exactly \(n\) literals and \(e_i\) and \(\overline{e}_i\) do not appear in \(T\) simultaneously for any \(1 \leq i \leq n\). Then, it could be verified that the set of objects each corresponding to a literal in \(T\) covers \(q.\psi\) and the cost of the set at most \(C\), and thus the answer of the CoSKQ problem is also “yes”. Suppose that the answer of the CoSKQ problem is “yes”. Let \(S\) be the set of objects in \(O\) that covers \(q.\psi\) and has the cost at most \(C\). We know that object \(o_i\) and \(o_i\) are not included in \(S\) simultaneously. It could be verified that with the truth assignment represented by the set of literals corresponding to the objects in \(S\), \(E\) is correct, and thus the answer of the 3-SAT problem is also “yes”.

APPENDIX C

PRUNING BASED ON DOMINANCE

To improve the efficiency of the algorithm, we propose a pruning strategy to prune the search space when \(\alpha = 1\) and \(\phi = 1\). Before we give the strategy, we first introduce the concept of dominance.

Given a query \(q\), two objects \(o_1\) and \(o_2\), we say \(o_1\) dominate \(o_2\) if the following two conditions are satisfied. (1) \(d(o_1, q) < d(o_2, q)\), and (2) all keywords in \(q.\psi\) that are covered by \(o_2\) can be covered by \(o_1\), i.e., \(q.\psi \cap o_1.\psi \supseteq q.\psi \cap o_2.\psi\). A dominant object is defined to be an object that is not dominated by any other objects.

Then we have the following lemma to prune the objects that are not dominant objects.

**Lemma 5.** When \(\alpha = 1\) and \(\phi = 1\), all objects in the optimal solution \(S\) are dominant objects.

**Proof:** We prove this by contradiction. Let an object \(o \in S\) that is not a dominant object. Then, there must exist an object \(o'\) that dominates \(o\). Note that \(o'\) also covers the query keywords covered by \(o\) and is closer to \(q\). We can construct a better solution \(S' = S \setminus o \cup o'\), which contradicts the fact that \(S\) is the optimal solution.

Based on this lemma, it is sufficient for the algorithm to consider the dominant objects only when enumerating the object sets. Specifically, whenever the algorithm performs a range query, it discards the objects that are being dominated and proceeds with the dominant objects.

APPENDIX D

BETTER IMPLEMENTATION BASED ON INFORMATION RE-USE

To implement the Unified-A algorithm efficiently, we have the following implementation strategies. First, when the algorithm finding
the set of all relevant objects in $R_o$ (line 5 in Algorithm 4), instead of issuing a range query in each iteration, it re-uses the information from the previous iteration by maintaining the region $R_o$ dynamically. Specifically, consider one iteration. The algorithm finds a feasible set that has an object $o$ as a key query-object distance contributor in the region $R_o$. After it finishes the current iteration, it adds $o$ into $R_o$ (when $\phi_1 \in [1, \infty]$), or removes $o$ from $R_o$ (when $\phi_1 = -\infty$).

Second, when the algorithm performs the iterative process (lines 8-14 in Algorithm 4), instead of searching for the object with minimum ratio (distance) from $\mathcal{O}$ in each iteration, it maintains a heap structure for storing the objects. Specifically, when $\phi_1 = 1$, the key of the objects in the heap are the ratios, and the heap is updated after each object is picked. When $\phi_1 \in \{-\infty, -\infty\}$, the key of the objects in the heap are the distances, and in each iteration the algorithm picks the relevant object with the smallest distance.

### APPENDIX E

**EXPERIMENTAL RESULTS ON THE DATASETS GN AND WEB**

In the following, we present the experimental results on the datasets GN and Web of varying $|q, \psi|$. Following the existing studies [3], [17], we vary the number of query keywords (i.e., $|q, \psi|$) from $\{3, 6, 9, 12, 15\}$.

1. **$\text{cost}_{\text{MinMax}}$**. The results for $\text{cost}_{\text{MinMax}}$ on the datasets GN and Web are shown in Figure 18 and Figure 19 respectively, which are similar to that on the dataset Hotel. The result of running time of Cao-E1 for $|q, \psi| = 15$ is not shown in Figure 19 simply because it ran for more than 10 hours (this applies for all the following results).

2. **$\text{cost}_{\text{MinMax2}}$**. The results for $\text{cost}_{\text{MinMax2}}$ on the datasets GN and Web are shown in Figure 20 and Figure 21 respectively, which are similar to those for $\text{cost}_{\text{MinMax}}$.

3. **$\text{cost}_{\text{Sum}}$**. The results for $\text{cost}_{\text{Sum}}$ on the datasets GN and Web are shown in Figure 22 and Figure 23 respectively. According to the results, Unified-E runs slower than Cao-E2 but still within a reasonable time (e.g. within 10 seconds on the largest dataset Web). Besides, Unified-A has a very similar running time as Cao-A3, while Unified-A can always obtain an approximation ratios of 1.

4. **$\text{cost}_{\text{SumMax}}$**. The results for $\text{cost}_{\text{SumMax}}$ on the datasets GN and Web are shown in Figure 24 and Figure 25 respectively, which are similar to that on the dataset Hotel.

5. **$\text{cost}_{\text{MaxMax}}$**. The results for $\text{cost}_{\text{MaxMax}}$ on the datasets GN and Web are shown in Figure 26 and Figure 27 respectively, which are similar to that on the dataset Hotel.

6. **$\text{cost}_{\text{MaxMax2}}$**. The results for $\text{cost}_{\text{MaxMax2}}$ on the datasets GN and Web are shown in Figure 28 and Figure 29 respectively, which are similar to that on the dataset Hotel.

7. **$\text{cost}_{\text{Max}}$**. The results for $\text{cost}_{\text{Max}}$ on the datasets GN and Web are shown in Figure 30 which is similar to that on the dataset Hotel. According to the results, both Unified-E and Unified-A run very fast, e.g. they ran less than 6 ms for all settings of $|q, \psi|$.
APPENDIX F
SCALABILITY TEST

(2) cost_{MinMax2}. The results for cost_{MinMax2} are shown in Figure 31. According to Figure 31(a), Unified-E is faster and more scalable than Cao-E1, e.g., on a dataset with 6M objects, Unified-E ran for a couple of seconds while Cao-E1 ran for more than 10 hours. Besides, similar to the case of cost_{MinMax}, Unified-A runs slightly slower than Cao-A1, but gives much better approximation ratio, e.g. the median of approximation ratios of Unified-A are 1 on all settings while that of Cao-A1 are larger than 1.

(3) cost_{sum}. The results for cost_{Sum} are shown in Figure 32. According to Figure 32(a), Unified-E is very scalable when the number of objects is large, e.g., it ran slightly longer than 1 second on a dataset with 10M objects. Besides, we noticed that Cao-E2 has a very good performance and it even runs as fast as the approximation algorithms. The reason could be as follows. With the number of objects grows, the number of relevant objects
becomes large. Both approximate algorithms have to re-compute the ratio for the remaining nodes in the heap and re-organize the heap after picking each object, whose cost becomes expensive when the number of relevant objects is large. In contrast, Cao-E2 maintains a heap structure though, it does not have to re-examine the nodes after processing a node. Unified-A has similar running times as Cao-A3 but gives better approximation ratios than Cao-A3 (Figure 32(b)). Specifically, Unified-A can achieve near-to-optimal approximation ratios on all setting while Cao-A3 has its largest approximation ratios up to 1.279.

(4) **cost\textsubscript{SumMax}.** Same as the experiments of varying $|o,\psi|$ for **cost\textsubscript{Sum},** we used the setting of $|q,\psi| = 8$ for the scalability test experiments for **cost\textsubscript{SumMax}.** Particularly, the results for **cost\textsubscript{SumMax}** are shown in Figure 35. According to Figure 35(a), Unified-E and Cao-E1 have similar running times and Unified-A and Cao-A3 also have similar running times, but Unified-A gives a better approximation ratio than Cao-A3 (Figure 35(b)).

(5) **cost\textsubscript{MaxMax}.** The results for **cost\textsubscript{MaxMax}** are shown in Figure 36. According to Figure 35(a), Unified-E runs faster than Long-E but slower than Cao-E1. According to Figure 35(b) and (c), Unified-A runs faster than Long-A and Cao-A2 and slower than Cao-A1, and Unified-A is one of the two algorithms (the other is Long-A which runs slower than Unified-A by about one order of magnitude) which give the best approximation ratios. Specifically, the largest approximation ratios of Unified-A is only 1.134, which is small, while that of Cao-A1 and Cao-A2 are 2.456 and 1.345, respectively.

(6) **cost\textsubscript{MaxMax2}**. The results for **cost\textsubscript{MaxMax2}** are shown in Figure 36. According to the results, both Unified-E and Unified-A runs very fast, e.g. they ran within 1 second on a dataset with 10M objects.