Constrained Skyline Query Processing against Distributed Data Sites

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Abstract—The skyline of a multidimensional point set is a subset of interesting points that are not dominated by others. In this paper, we investigate constrained skyline queries in a large-scale unstructured distributed environment, where relevant data are distributed among geographically scattered sites. We first propose a partition algorithm that divides all data sites into incomparable groups such that the skyline computations in all groups can be parallelized without changing the final result. We then develop a novel algorithm framework called *PaDSkyline* for parallel skyline query processing among partitioned site groups. We also employ intragroup optimization and multifiltering technique to improve the skyline query processes within each group. In particular, multiple (local) skyline points are sent together with the query as filtering points, which help identify unqualified local skyline points early on a data site. In this way, the amount of data to be transmitted via network connections is reduced, and thus, the overall query response time is shortened further. Cost models and heuristics are proposed to guide the selection of a given number of filtering points from a superset. A cost-efficient model is developed to determine how many filtering points to use for a particular data site. The results of an extensive experimental study demonstrate that our proposals are effective and efficient.

Index Terms—Constrained skyline query, filtering point, distributed query processing.

1 Introduction

Given a multidimensional point set, a skyline query [1] returns all *interesting* points that are not *dominated* by any other points. A point pt_1 is said to dominate pt_2 if pt_1 is not worse than pt_2 in every single dimension but better than pt_2 in at least one dimension. The implication of "better" varies in different contexts. For example, "better" can mean "smaller" or "larger" in value comparison, and "earlier" or "later" in date comparison.

Because of their powerful capability of retrieving interesting points from a large multidimensional data set, skyline queries are well suitable for applications like multiple criteria optimization. Skyline queries play an important role in multicriteria decision making and user preference applications. For instance, a tourist can issue a skyline query on a hotel relation to get those hotels with high stars and cheap prices.

Most works on skyline queries [1], [2], [4], [5], [6], [7] so far have assumed a centralized data storage, and been focused on providing efficient skyline computation algorithms on a sole database. This assumption, however, fails to reflect the distributed computing environments consisting of different computers, which are located at geographically scattered sites and connected via Internet.

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For example, a stock trader needs to know which stocks worldwide are worth investing, based on the trading records of the previous day. For this purpose, she needs to access multiple stock information databases available at different places like New York Stock Exchange, London Stock Exchange, Tokyo Stock Exchange, etc. For each single stock, the agent needs to take into consideration multiple attributes like *last trade price*, *change*, *last close price*, *estimated price*, *volume*, etc. Therefore, a skyline query against those distributed databases will help the agent get those interesting stocks.

Another example is online comparative shopping in which a search engine needs to get good bargains from many different shopping sites according to multiple criteria like *price*, *quality*, *guarantee*, etc. Clearly, such multiple criteria are best captured by a skyline query.

For the aforementioned tourist looking for interesting hotels, she may issue her skyline query on a tourism website, which in turn, accesses data from many other sites with hotel relations. In this example, efficient skyline queries against those distributed relations will give tourists good user experiences with the tourism website, and thus, attract them to pay revisits.

In such example cases, however, directly applying existing centralized skyline approaches to process distributed skyline queries would incur large overheads. Such approaches assume a sole relation as input, and lack adaptations or optimizations specific to distributed computing environments.

In this work, we intend to efficiently process constrained skyline queries [6] in such widely distributed environments. A constrained skyline query is attached with constraints on specific dimensions. A constraint on a dimension is a range specifying the user's interest. Refer again to the stock selection example. The agent may only be interested in those stocks whose *last trade prices* are between \$15 and \$20. Similar

constraints are also applicable to other dimensions. Note that the range denoted by a constraint can be unclosed, like *estimated price* higher than \$20. Also, constraints may be available in only part of the total n dimensions.

Given a distributed environment without any overlay structures, our objective is efficient query processing strategies that shorten the overall query response time. We first speed up the overall query processing by achieving parallelism of distributed query execution. Given a skyline query with constraints, all relevant sites are partitioned into incomparable groups among which the query can be executed in parallel. The parallel execution also makes it possible to report skyline points progressively, which is usually desirable to users.

Within each group, specific plans are proposed to further improve the query processing involving all intragroup sites. On a processing site, multiple filtering points are deliberately picked based on their overall dominating potential from the local skyline. They are then sent to other sites with the query request, where they help identify more unqualified points that would otherwise be reported as false positives, and thus, reducing the communication cost between data sites.

We make the following contributions in this paper:

- We propose a specific partition algorithm that divides all relevant sites into groups such that a given query can be executed in parallel among all those site groups. We elaborate on the intragroup query execution strategies. We then give a parallel distributed skyline algorithm, together with a cost model to estimate the overall query response time.
- We detail heuristics for selecting a given number of multiple filtering points in distributed query processing such that the amount of data to be transmitted via the network is reduced.
- We propose a cost-efficient model for dynamically determining the number of filtering points to be sent to a particular site such that the benefit of using filtering points is maximized.
- We conduct an extensive experimental study on both synthetic and real data sets, and the results demonstrate the effectiveness, efficiency, and robustness of our proposals.

This paper extends a preliminary work [3] in several substantial ways. First, we present detailed algorithm and enhance it for the intragroup query execution. Second, we analyze the problem of two basic heuristics for filtering points selection and propose the improvements accordingly. Third, we propose a cost-efficient model for dynamically determining the number of filtering points to be sent to a particular site. Fourth, we redesign the experimental study and conduct more extensive experiments with regard to technical extensions.

The remainder of the paper is organized as follows: Section 2 gives the problem definition and provides a brief review of related work on skyline queries. Sections 3 presents the parallel distributed query execution. Section 4 elaborates on the selection of a given number of multiple filtering points. Section 5 details the cost-efficient model for determining the beneficial number of filtering points to use. Section 6 presents the experimental results, followed by the conclusion in Section 7.

2 Preliminaries

2.1 Problem Definition

Given a set of m sites $\mathcal{S} = \{S_1, S_2, \ldots, S_m\}$ distributed at different geographic locations, each S_i has a local relation R_i. Every tuple in any R_i is an n-dimensional point, represented as $(p_1, p_2, \ldots, p_n)$. Different R_is may overlap, i.e., it is possible that $R_i \cap R_j \neq \emptyset$ for $i \neq j$.

Without loss of generality, we assume that smaller values are preferred in the skyline operator. We use $pt_1 \prec pt_2$ to represent point pt_1 dominates point pt_2. In addition, we suppose any site S_{org}, able to directly communicate with any other site $S_i \in \mathcal{S}$ through wired end-to-end connections, may initiate against all R_is a skyline query with a set of n constraints $\mathcal{C} = \{C_1, C_2, \ldots, C_n\}$. Each C_i is either a range $[l_i, u_i]$, or a $\emptyset$ indicating no constraint in that dimension. Our goal is to get the result for the constrained skyline query efficiently, i.e., with short response time. We define the query response time as the time period from the moment a query is issued by a site S_{org} to the moment S_{org} receives the complete and correct answers after contacting other sites.

To shorten the response time of a query, we mainly endeavor on two aspects. On one hand, we propose effective ways to guide deciding the query forwarding and execution order between different sites, so as to obtain the query execution parallelism, and boost the result reporting progressiveness. On the other hand, we generalize the single filtering point idea [13] to use multiple filtering points, and thus, enhancing the filtering power and reducing the amount of data transmitted between remote sites. We propose benefit measurements and heuristics to guide the determination of the number of filtering points to use and selection of powerful multiple filtering points.

In contrast to previous work [12], [10], our problem definition does not assume the availability of an overlay network, where different nodes hold disjoint data partitions. Instead, different relations on different sites may overlap. Therefore, these previous methods are not applicable to our problem.

2.2 Related Work

Borzonyi et al. [1] introduced the skyline operator into database systems with algorithms *Block Nested Loop* (BNL) and *Divide-and-Conquer* (D&C). Chomicki et al. [2] proposed a *Sort-Filter-Skyline* (SFS) algorithm as a variant of BNL. Tan et al. [7] proposed two progressive algorithms: *Bitmap* and *Index*. The former represents points in bit vectors and employs bitwise operations, while the latter utilizes data transformation and B^+-tree indexing. Kossmann et al. [5] proposed a *Nearest Neighbor* (NN) method. It identifies skyline points by recursively invoking R^*-tree-based depth-first NN search over different data portions. Papadias et al. [6] proposed a *Branch-and-Bound Skyline* (BBS) method based on the best-first nearest neighbor algorithm [8]. Godfrey et al. [4] provided a comprehensive analysis of previous skyline algorithms without indexing supports,

and proposed a new hybrid method with improvement. All these works assume centralized data storage.

Deviating from skyline queries in the centralized setting, Balke et al. [9] addressed skyline operation over web databases, where different dimensions are stored in different data sites. Their algorithm first retrieves values in every dimension from remote data sites using sorted access in round-robin on all dimensions. This continues until all dimension values of an object, called the terminating object, have been retrieved. Then all nonskyline objects will be filtered from all those objects with at least one dimension value retrieved. Differently in this paper, our work deals with distribution of data horizontally partitioned.

Wu et al. [10] proposed a parallel execution of constrained skyline queries in a CAN [11] based distributed environment. By using the query range to recursively partition the data region on every data site involved, and encoding each involved (sub)region dynamically, their method avoids accessing sites not containing potential skyline points and progressively reports correct skyline points. Wang et al. [12] developed Skyline Space Partitioning (SSP) approach to compute skylines on a tree-structured P2P platform BATON. SSP partitions the skyline space into regions and maps them in a single-dimensional order, which allows regions to be distributed to different peer nodes according to BATON protocols. Our proposal in this paper differs from these two pieces of work in that we do not assume any overlay availability on top of the original network.

Huang et al. [13] proposed techniques for skyline query processing in MANETs. Lightweight devices in MANETs are able to issue spatially constrained skyline queries that involve data stored on many mobile devices. Queries are forwarded through the whole MANET without routing information. They proposed a filtering-based data reduction technique that reduces the data transferred among devices. Our work, assuming a wired large-scale distributed environment, is also different from this work in a MANET setting. Zhu et al. [21] proposed a feedback-based distributed skyline (FDS) algorithm within a network setting similar as ours. However, FDS only deals with skyline queries without any constraints that are considered in our work. Also, FDS is focused on minimizing the network bandwidth use, and therefore, it uses a multiple-round feedback mechanism to prune the unqualified skyline candidates. When the network becomes large, the delay (i.e., the query response time) of FDS will increase considerably. In contrast, our work applies a one-round filtering technique that is aimed to reduce the network delay.

3 Skyline Processing against Distributed Data Sites

3.1 Motivation

In a previous work [13], a skyline query is forwarded among mobile peers via multiple hops in a MANET. Whereas in a wired environment, connections are end-to-end. Because of such wired connections between each pair of sites, a constrained skyline query can be sent out to all peer sites and then each site can execute the query on its own data set simultaneously. This naive execution plan might benefit from the parallelism among all peer sites. However, it is very sensitive to large local skyline results, usually of but not limited to anticorrelated data sets [1], which lead to heavy communication cost. For this reason, identifying unqualified candidates in local skylines early is favorable.

Following the data reduction principle in semijoin in distributed query processing [14], Huang et al. [13] proposed to transfer a single local skyline point with the query request among mobile peers, which acts as a filter to identify those unqualified ones in peers' local skylines. In this work, we extend this single filtering point to multiple ones since wired connections are much faster and more reliable than wireless channels. How to choose multiple filtering points will be detailed in Section 4. In this section, we focus on finding a good distributed skyline query execution plan that minimizes the total execution time.

We argue that the order to execute a distributed skyline query among multiple sites really matters because an appropriate execution order can filter more data points earlier, and thus, reducing not only communication cost but also the local processing cost in the subsequent execution. We intend to balance the parallelism and filtering when processing a distributed skyline query (DSQ) and get short overall response time.

3.2 Parallel Distributed Query Execution

To help determine execution order among different sites, the query originator first asks each site S_i for its MBR_i, the n-dimensional minimum bounding box of the local relation R_i. If a site's MBR disjoins with the constraint set $\mathcal{C}$ specified in the query, it will not be considered in the following query processing. For each site whose MBR_i overlaps with $\mathcal{C}$, we only need to consider the intersection $MBR_i \cap \mathcal{C}$. We call this intersection *reduced minimum bounding box* and use $rMBR_i$ to represent it.

We proceed to partition all those sites left into several groups according to their $rMBR$s such that the skyline computation in any one group does not depend on or affect the computation in any other group. Therefore, the given skyline query can be executed in parallel among those site groups. While within any individual site group, the query is executed according to some local plans, which will be discussed in Section 3.2.2.

3.2.1 Incomparable Partition of Sites and Parallelism

Given two data sites S_i and S_j (with their reduced minimum bounding boxes $rMBR_i$ and $rMBR_j$, respectively), we need to determine if the skyline query can be executed against them in a parallel way such that two results do not affect each other. Intuitively, we cannot do this if they overlap, as in the overlapping region points from different boxes may be not incomparable. Whereas, the nonoverlapping relationship does not necessarily permit parallelism. To handle this problem, we first give a definition of "incomparable" between two data sites.

Definition 1. *Two data sites S_i and S_j are incomparable with respect to the constrained skyline query iff $rMBR_i.min.DR \cap rMBR_j = \emptyset$ and $rMBR_j.min.DR \cap rMBR_i = \emptyset$.*

In Definition 1 above, $rMBR_i.min.DR$ stands for the dominating region of $rMBR_i$'s minimum corner with respect to the constraints specified in the skyline query. It

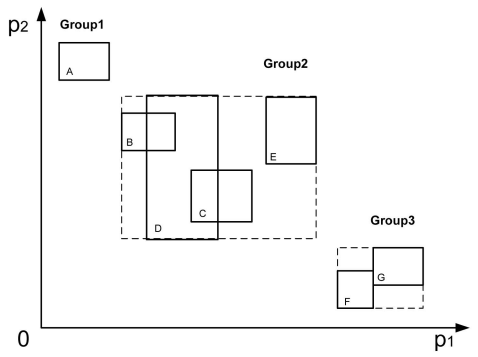

Fig. 1. Incomparable partition of sites.

is obtained as the intersection of the original dominating region [13] and the set of constraints $\mathcal{C}$, which will be formalized in Section 4.1.1. When there is no confusion or ambiguity in the context, we also say that two reduced minimum bounding boxes $rMBR_i$ and $rMBR_j$ are incomparable, which actually means that their corresponding data sites are incomparable. With this definition, we have the following lemma:

Lemma 1. *If two data sites S_i and S_j are incomparable with respect to the constrained skyline query, it holds that $\forall pt_i \in rMBR_i$, $\nexists pt_j \in rMBR_j$ s.t. $pt_i \prec pt_j$ and $\forall pt_j \in rMBR_j$, $\nexists pt_i \in rMBR_i$ s.t. $pt_j \prec pt_i$.*

The correctness of this lemma is guaranteed by the property that the minimum corner of $rMBR$ has the strongest dominating capability among all possible points in $rMBR$. This lemma shows that a given skyline query can be executed against two incomparable sites in parallel without conflict between the results. It is easy to see that this parallelism can be generalized to multiple sites, any pair of which are incomparable. A by-product of this parallelism is the progressiveness of skyline reporting, since the result of any single site among those pairwise incomparable sites definitely appears in the final skyline.

As we do not assume any specific partition among all sites, it is possible that all sites are not pairwise incomparable. Thus, we partition the set of sites $\mathcal{S}$ into nonempty groups that satisfy: 1) Any pair of sites from different groups are incomparable. 2) For any pair of sites S_i and S_j within the same nonsingleton group, there exists a path $S_i, S_k, \ldots, S_j$ such that any adjacent pair along the path are not incomparable. Property 1 ensures that parallel execution can be carried out against groups of sites. While property 2 clusters together those sites whose local skyline results potentially conflict, and provides opportunity for alternative optimizations. We call the partition *incomparable partition* of sites.

The partition algorithm, $icmpPartition$ for short, is shown in Algorithm 1. Before the real partitioning, intersections of site MBRs and constraint set $\mathcal{C}$ are obtained with unpromising sites being pruned (lines 1-4). The algorithm starts by assigning the first candidate site to a singleton group (line 5). Then, each remaining site S_i is compared with every current group, and any group containing sites not incomparable with S_i is removed from the partition into a temporary group $\overline{\mathcal{S}_i}$ (lines 6-11). At the end of each loop, S_i is assigned to the adjusted partition, either in a new singleton group or in the temporary group with other relevant sites found in the loop (line 12). Given all site MBRs and the constraint set, the group formation (group number and compositions) is deterministic accordingly. Our partitioning algorithm obtains the group formation exactly.

Algorithm 1: `icmpPartition(`$\mathcal{S}, \mathcal{C}$`)`

Input: $\mathcal{S}$ is the set of data sites;
$\mathcal{C}$ is the set of constraints in the skyline query;
Output: an incomparable partition of $\mathcal{S}$;

```
// Adjust MBRs and prune unqualified sites
1  for each S_i ∈ S do
2      rMBR_i = MBR_i ∩ C;
3      if rMBR_i == ∅ then
4          S = S − {S_i};
// Compute the independent partition of all
   relevant sites
5  Π_S = {{S_1'}};   // S_1' is the current 1st element in S;
6  for each S_i ∈ S − {S_1'} do
7      S̄_i = ∅;
8      for each S_i ∈ Π_S do
9          if ∃S_j ∈ S_i s.t. S_j and S_i are not incomparable then
10             Π_S = Π_S − {S_i};
11             S̄_i = S̄_i ∪ S_i;
12     Π_S = Π_S ∪ {{S_i} ∪ S̄_i};
```

Example 1. Refer to an example in two-dimensional space shown in Fig. 1, where $\mathcal{S} = \{A, B, C, D, E, F, G\}$. Each site's MBR is shown in a corresponding rectangle. Based on the incomparableness related properties above, $\mathcal{S}$ is partitioned into $\{\{A\}, \{B, C, D, E\}, \{F, G\}\}$. A forms a singleton group because it is incomparable with any other site. Though B and C are incomparable, they are assigned to the same group with D and E, because either of them is not incomparable with D (and E). F and G are incomparable with any other site but not with each other, therefore, they constitute another group.

3.2.2 Intragroup Query Execution

Within each group of the sites obtained above, we need to consider the execution order among those relevant sites. Now effective filtering is our concern, in other words, we use filtering points when forwarding a DSQ between sites in the same group. Given a group $\mathcal{S}_i = \{S_{i_1}, \ldots, S_{i_k}\}$, we have two alternatives for intragroup execution order.

A simple way is to decide a sequence of these sites and forward the DSQ with filtering points along the sequence. The sequence is gained by sorting all sites S_{i_j}s in a nondescending order of the euclidean distance between the minimum corners of $rMBR_{i_j}$ and constraints set $\mathcal{C}$. The reason for this lies in the intuition that a point nearer to the minimum corners of $\mathcal{C}$ (or the origin when a skyline query without constraints is concerned) is more powerful in terms of dominating capability. The sorting can be integrated into the partition algorithm in Algorithm 1, on line 12, where $\overline{\mathcal{S}_i}$ and $\mathcal{S}_i$ ($\{S_i\}$) are united.

Example 2. Refer to Example 1, we use the second group $\{B, C, D, E\}$ as an example, shown in Fig. 2a. Constraint

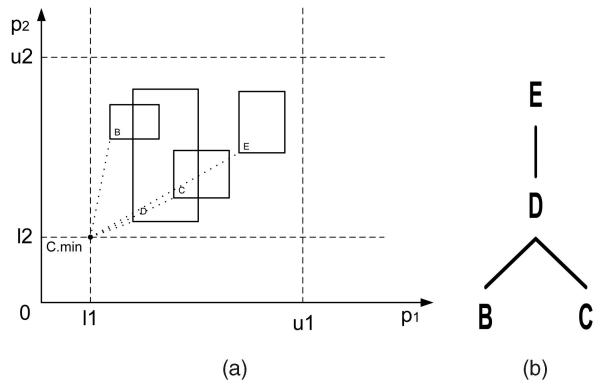

Fig. 2. Intragroup execution. (a) Sites sorting. (b) Tree structure.

set $\mathcal{C} = ([l_1, u_1], [l_2, u_2])$ is displayed with dashed lines. The minimum corner of $\mathcal{C}$ is displayed as $C.min$. In Fig. 2a, we can see that the euclidean distance between the minimum corner of $rMBR_D$ and $C.min$ is the shortest one among all such distances. As a result, this group can be sorted in a nondescending order as $\{D, C, B, E\}$.

The linear approach ignores any internal possibilities for parallelism. In Fig. 1, for example, the query can be parallelized against sites B and C either before or after other sites. To fully capture this potential for intragroup parallelism, a directed graph is needed to store all sites in a group, which is quite complicated due to the nature of a graph. As a trade-off between complexity and parallelism, we use a tree to organize each group of sites. For this purpose, we adapt the partition algorithm in Algorithm 1 as follows: In each loop (lines 8-12) on site S_i, instead of using a temporary group $\overline{S_i}$ to contain the union of all groups removed out from $\Pi_{\mathcal{S}}$, S_i is used as a root and all such groups are attached to it as children, and finally, the tree is added into the partition as an updated group. After the partitioning, within every group, the query is executed and forwarded with filtering points in the top-down manner starting from the root. The adapted algorithm is shown in Algorithm 2.

Algorithm 2: `icmpPartition2(`$\mathcal{S}, \mathcal{C}$`)`

Input: $\mathcal{S}$ is the set of data sites;
$\mathcal{C}$ is the set of constraints in the skyline query;
Output: an incomparable partition of $\mathcal{S}$;

```
// Adjust MBRs and prune unqualified sites
```
1 **for each** $S_i \in \mathcal{S}$ **do**
2 $rMBR_i = MBR_i \cap \mathcal{C}$;
3 **if** $rMBR_i == \emptyset$ **then**
4 $\mathcal{S} = \mathcal{S} - \{S_i\}$;

```
// Compute the independent partition of all
   relevant sites
```
5 $\Pi_{\mathcal{S}} = \{\{S_{1'}\}\}$; // $S_{1'}$ is the current 1^{st} element in $\mathcal{S}$;
6 **for each** $S_i \in \mathcal{S} - \{S_{1'}\}$ **do**
7 $tree.Root = S_i$;
8 **for each** $\mathcal{S}_i \in \Pi_{\mathcal{S}}$ **do**
9 **if** $\exists S_j \in \mathcal{S}_i$ *s.t.* S_j *and* S_i *are not incomparable* **then**
10 $\Pi_{\mathcal{S}} = \Pi_{\mathcal{S}} - \{\mathcal{S}_i\}$;
11 $tree.addSubTree(Root, \mathcal{S}_i)$;
12 $\Pi_{\mathcal{S}} = \Pi_{\mathcal{S}} \cup \{tree\}$;

Example 3. Refer to Example 1 and group $\{B, C, D, E\}$ again. According to Algorithm 2, sites B and C are first partitioned into two different groups. And then, they are attached to D as subtrees because both of them are not incomparable with site D. At the end, the tree rooted at D is attached to E as a subtree because D and E are not incomparable. The tree structure of the result is shown in Fig. 2b. In this tree, sites B and C are executed in parallel after E and D.

In either the linear approach or the tree-based approach, every group needs an assembly to merge results from sites and remove false positives during the query processing. We install this procedure in the *group head* site. The head site is responsible for returning result to query originator. It is the first site in the linear approach, or the root site in the tree-based approach.

3.3 Parallel Distributed Skyline Algorithm

Based on the discussion so far, our overall parallel distributed skyline algorithm, called PaDSkyline, is presented in Algorithm 3. When a site S_{org} issues a distributed skyline query with constraints $\mathcal{C}$, it first gets the incomparable partition of all sites by calling icmpPartition (line 1). After that, the query request will be sent out to each group head in parallel (lines 2 and 3). The query request includes constraints $\mathcal{C}$, network addressable query originator identifier S_{org}, and the intragroup query execution plan $g_i.plan$. Next, S_{org} enters a wait during which it will be triggered by an incoming result reply from a group head, until all of them have replied (lines 4-7). When receiving the reply from the head of group g_i, S_{org} directly reports the result $g_i.result$ (lines 5 and 6) as it is incomparable with results from other groups.

Algorithm 3: `PaDSkyline(`$\mathcal{S}, \mathcal{C}$`)`

Input: $\mathcal{S}$ is the set of data sites;
$\mathcal{C}$ is the set of constraints in the skyline query;
Output: the constrained skyline;
1 $\Pi_{\mathcal{S}}$ = icmpPartition($\mathcal{S}$, $\mathcal{C}$);

```
// parallel execution
```
2 **for** ***each*** *group* $g_i \in \Pi_{\mathcal{S}}$ *in parallel* **do**
3 send $\langle \mathcal{C}, S_{org}, g_i.plan \rangle$ to g_i's group head;

```
// result merge, triggered by incoming
   result reply
```
4 **repeat**
5 receive result reply from a group g_i's head;
6 report $g_i.result$;
7 **until** all group heads have replied;

For the sake of simplicity, we designate S_{org} as the head of its site group. The network communication between S_{org} and a group head degrades to an interprocess or interthread communication on a single host.

After a group g_i's head receives the query request, it carries out the intragroup skyline computation as shown in Algorithm 4. First, it computes its local constrained skyline R_g and captures the initial filtering points set $F_{\mathcal{C}}$ during the local computation (line 1). How to select multiple filtering points will be detailed in Section 4. Next, it sends the query request further to downstream site(s) in the group query plan (line 2). Note here that the query request includes the constraints $\mathcal{C}$, network addressable group head's identifier S_g, the reduced query plan $plan'$, and the initial filtering points set $F_{\mathcal{C}}$. Each site S_i receiving the query request computes its local result $S_i.R$, returns $S_i.R$ to site S_g, and

sends the query request with updated filtering points and further reduced plan to its own downstream site(s). While S_g keeps receiving $S_i.R$ and merging it with R_g until all group members have replied (lines 3-6).

Algorithm 4. `groupSkyline`$(\mathcal{C}, S_{org}, plan)$
Input: $\mathcal{S}$ is the set of data sites;
$\mathcal{C}$ is the set of constraints in the skyline query;
$plan$ is the query execution plan in the group;
Output: the constrained skyline within the group;
1 compute local skyline R_g and get the initial filtering points set $F_{\mathcal{C}}$;
2 send $\langle \mathcal{C}, S_g, plan', F_{\mathcal{C}} \rangle$ to next site(s) in $plan$;
3 **repeat**
4 receive result reply from a group member S_i;
5 merge $S_i.R_i$ with R_g,
6 removing duplicates and false positives;
7 **until** all group members have replied;
8 **return** R_g to S_{org};

During query execution within a site group, the filtering points set $F_{\mathcal{C}}$ can be dynamically changed. Also, the query plan can be dynamically reduced as follows: Each site, including the group head, removes itself from the plan. If the plan is a single sequence, the reduced plan is the subsequence left and its head is exactly the target downstream site. If the plan is a tree, the removal may result in more than one subtree. For that case, each of them will be sent to a corresponding target downstream site, which is exactly the root of a subtree.

3.4 Cost Model for Query Response Time

Suppose that the time to compute the local skyline SK_i is $T_l(R_i)$ on a local relation R_i. We use "$|SK_i|$" to represent the size in bytes of a local skyline. The time to transfer SK_i between two sites is determined by its size, together with the relevant network conditions like bandwidth.

In the naive approach without filtering (see Section 3.1), the time for query originator S_{org} to get result from a peer site S_i is the sum of the local computation time and network transmission time, as shown in the following (1):

$$T_i = T_l(R_i) + T_{tran_{i,org}}(|SK_i|). \tag{1}$$

Due to the parallelism of a naive query execution, its overall response time T_{nav} is determined by the peer site whose result reaches S_{org} latest and the local assembly time on S_{org}, as shown in the following (2):

$$T_{nav} = max\{T_i \mid 1 \le i \le m\} + T_{asm}. \tag{2}$$

Suppose that an incomparable partition $\Pi_{\mathcal{S}} = \{\mathcal{S}_1, \ldots, \mathcal{S}_k\}$ is produced for a given distributed skyline query with constraints. Its overall response time T_{pdq} is determined by the group whose result reaches S_{org} latest, as shown in (3). Note that in the parallel distributed query processing, we do not need a global assembly on S_{org}:

$$T_{pdq} = max\{T_{\mathcal{S}_i} \mid 1 \le i \le k\}. \tag{3}$$

In the formula above, $T_{\mathcal{S}_i}$ is the response time of group $\mathcal{S}_i$, i.e., the time lapse before S_{org} receives the result from $\mathcal{S}_i$'s group head h_i. It is detailed in (4). Here, T_{h_i} is the local response time, i.e., the time lapse before h_i gets all results from sites in the group, $T_{asm_{h_i}}$ is the local assembly time, and $SK_{\mathcal{S}_i}$ is the result sent to S_{org}:

$$T_{\mathcal{S}_i} = T_{h_i} + T_{asm_{h_i}} + T_{tran_{h_i,org}}(|SK_{\mathcal{S}_i}|). \tag{4}$$

The naive approach has two main disadvantages. First, it has to transmit all unreduced local skylines. Second, it has to assemble all local skylines on S_{org}. In contrast, our distributed approach sends less data among sites, and conducts assembly in parallel in multiple groups.

4 Data Reduction Using Multiple Filtering Points

One single filtering point is transferred and changed from peer to peer in [13]. During the query forwarding and processing, the single filtering point is dynamically changed once another point is found to be more powerful in filtering out unqualified candidates.

Data sites in this work, in contrast, are wired with considerably steady and high bandwidth compared to wireless MANETs. This allows us to use multiple filtering points among sites, as data transmission cost via wired connections is lower and multiple filtering points are expected to have higher filtering power. Consequently, we need to decide which and how many skyline points should be used as filtering points in the distributed skyline query processing such that the benefit is maximized.

In this section, we formalize the dominating region of multiple skyline points with respect to constraints, and address how to select a given number of filtering points initially. In Section 5, we study how many filtering points are adequate for a particular data site.

4.1 Dominating Capability of K Filtering Points

Filtering points are selected from the local skyline result initially obtained. Suppose that the initial skyline result is $SK_{init} = \{s_1, s_2, \ldots, s_l\}$, we need to select K ($<l$) points from it as the multiple filtering points. The concrete value of K is constrained by l and has effect on network communication cost and pruning capability obtained. The determination of K value is addressed in Section 5.1.

4.1.1 Dominating Region with Constraints

When K equals 1, we select the point with the maximum potential of dominating others, which is measured by the volume of a point's *dominating region*, the hyperrectangle determined by the point and the maximum corner of the data space [13].

In the presence of the constraints specified for relevant dimensions, the definition of dominating region needs amendments accordingly. As shown in Fig. 3, suppose that a constraint range $[l_1, u_1]$ is specified on the dimension p_1. Consequently, for a point tp_j ($<p_{j1}, \ldots, p_{jn}>$), its dominating region shrinks to the smaller one determined by its own value, constraint upper bound u_1, and dimension p_2's upper bound b_2.

Suppose that the value range on dimension p_k is $[s_k, b_k]$ in terms of all R_is. Then the volume of tuple tp_j's dominating region with respect to constraints is

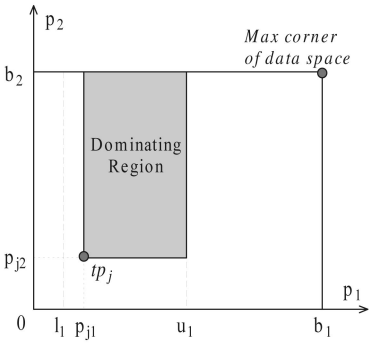

Fig. 3. Dominating region with constraints.

$$\widetilde{VDR}_j = \prod_{k=1}^{n}(\widetilde{b}_k - p_{jk}), \tag{5}$$

where

$$\widetilde{b}_k = \begin{cases} b_k, & \text{if } C_k = \emptyset, \\ u_k, & \text{if } l_k \le p_{jk} \le u_k, \\ p_{jk}, & \text{otherwise.} \end{cases}$$

Note that it does not make sense to define the dominating region for points out of the region specified by all constraints because such points do not appear in the skyline result and will not be considered when we select filtering points. In (5), we ensure that the $\widetilde{VDR}$ value is zero for any point uncovered by given constraints, which will prevent it from being chosen as a filtering point.

Given a collection of skyline points $\{s_1, s_2, \ldots, s_k\}$, their dominating regions only differ on their own positions in the data space. Thus, for any s_i in that collection, its dominating region is represented by a hyperrectangle $HR_i([p_{i1}, \widetilde{b}_1], \ldots, [p_{in}, \widetilde{b}_n])$, where $\widetilde{b}_i$ is determined as (5) describes.

4.1.2 Fused Dominating Region

For multiple filtering points, we need to consider their overall filtering capability, which is measured by the volume of their fused dominating region. Given any two distinct skyline points s_i and s_j, the volume of their fused dominating region is

$$\widetilde{VDR}_{i,j} = \widetilde{VDR}_i + \widetilde{VDR}_j - \prod_{k=1}^{n}(\widetilde{b}_k - max(p_{ik}, p_{jk})). \tag{6}$$

By applying the Inclusion-Exclusion principle further, we can compute the volume of fused dominating region of arbitrary number (K) of skyline points:

$$\widetilde{VDR}_{1..K} = \sum_{i=1}^{K}\widetilde{VDR}_i + \sum_{j=2}^{K}((-1)^{j-1} \sum_{1\le i_1<\cdots<i_j\le K}\prod_{k=1}^{n}(\widetilde{b}_k - max(p_{i_1k}, \ldots, p_{i_jk}))). \tag{7}$$

We call it *fused $\widetilde{VDR}$ value* for K skyline points. Basically, the computation complexity of (7) is $\mathcal{O}(2^K)$, which is quite high. What makes it even more complex is that the optimal selection of multiple filtering points is made by choosing points with the maximum volume of fused dominating region. For that purpose, we need to enumerate all $\binom{l}{K}K$-combinations of SK_{init}, whose computation complexity is $\mathcal{O}((\frac{e\cdot l}{K})^K)$. Hence, the total complexity of computing the fused $\widetilde{VDR}$ values for all K-combinations is $\mathcal{O}((\frac{2\cdot e\cdot l}{K})^K)$. This high complexity renders undesirable the optimal selection of K filtering points with the maximum fused $\widetilde{VDR}$ value. Therefore, we turn to alternatives that make more computationally efficient selections at the cost of the quality of the results.

4.2 Heuristics for Selecting K Filtering Points

In this section, we study heuristics that guide the selection of K filtering points from $l(>K)$ skyline points. Note that our goal here is to maximize the collective filtering power of K filtering points, which differs from the criteria used in selecting K most representative skyline points [17], [19].

4.2.1 Two Basic Heuristics

The first heuristic for selecting multiple filtering points maximizes the sum of the K $\widetilde{VDR}$ values of all possible choices. To accomplish this, we need to sort points in SK_{init} in a nonascending order and then pick the top-K ones. In an alternative way, the sorting can be integrated into the skyline computation, which produces a sorted SK_{init} for easy picking of top-K points. For both ways, the time complexity depends on the sorting method used, which usually does not go beyond $\mathcal{O}(l^2)$.

We call this heuristic *MaxSum*. It actually simplifies the computation by ignoring the overlapping between different skyline points' dominating regions. In other words, the overlapping between dominating regions determines the accuracy of this approximation. The smaller the overlapping regions are, the more accurate the method will be.

In the second heuristic, we intend to take into account the topology between filtering points, to reduce the overlapping faced by the first heuristic. Distance is a simple metric to help consider this. Intuitively, the farther two skyline points are apart, the less their dominating regions overlap. Hence, we propose a greedy heuristic, *MaxDist* for short, which maximizes the distance between filtering points.

Algorithm 5: `maxDist(`SK_{init}`,` K`)`

Input: SK_{init} is the initial skyline;
K is the number of filtering points needed;
Output: a set of multiple filtering points;

1 $F_{flt} = \emptyset$;
2 Pick s_i and s_j from SK_{init} satisfying $|s_i, s_j| \ge |s_{i'}, s_{j'}|$, $\forall\ 1 \le s_{i'}, s_{j'} \le l$;
3 $F_{flt} = \{s_i, s_j\}$; $SK' = SK_{init} - \{s_i, s_j\}$;
4 **while** $|F_{flt}| < K$ **do**
5 Pick s_i from SK' satisfying $\sum_{s_j \in F_{flt}} |s_i, s_j| \ge \sum_{s_j \in F_{flt}} |s_{i'}, s_j|$, $\forall\ s_{i'} \in SK'$;
6 $F_{flt} = F_{flt} \cup \{s_i\}$; $SK' = SK_{init} - \{s_i\}$;
7 **return** F_{flt}

The algorithm of this heuristic is shown in Algorithm 5. Initially, it picks from SK_{init} two points between which the distance is the largest among all pairs (line 2). Then, it incrementally selects points from SK_{init} and adds them to the filtering set, until K filtering points are obtained. In

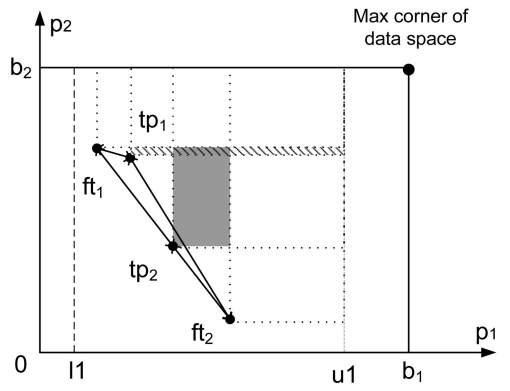

Fig. 4. Example of filtering points selection.

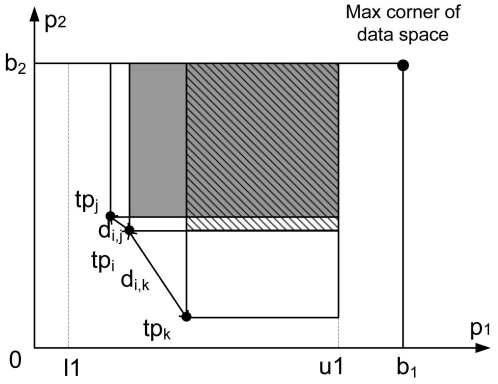

Fig. 5. Distance of filtering points.

every incremental step, the point with the maximal sum of distances to all current filtering points is selected (line 5). The time complexity of this algorithm is $\mathcal{O}(l^2)$, much less than the exact approach in Section 4.1.2.

4.2.2 Improvement of Filtering Points Selection

Both MaxSum and MaxDist heuristics are intended to select the K filtering points with maximum filtering capability. However, the former suffers from the overlaps among K filtering points, which reduces their filtering power. The latter alleviates the problem by maximizing the distance between filtering points.

The idea behind MaxDist heuristic is good, but it is difficult to implement strictly due to its computational complexity. Therefore, we count the sum of distance between a point and all current filtering points in MaxDist, and then pick the one with the maximum sum as a new filtering point. Though this indeed helps choose K filtering points with more filtering power, there is still room for further improvement.

Refer to Fig. 4, where a total of three filtering points are needed, and ft_1 and ft_2 are two already selected. If we select the third filtering point according to heuristic MaxDist, it is clear that tuple tp_1 is selected because it has the larger sum of distances to the existing filtering points. However, most portion of the dominating region of tp_1 is overlapping with that of ft_1. In other words, selecting tp_1 as a new filtering point only gives very little additional filtering power.

In contrast, if we choose tp_2 to be the new filtering point, a much larger extra region will be included to enlarge the fused dominating region of the filtering points, as shown in gray rectangle in Fig. 4. This will enhance the filtering power of the three filtering points.

We proceed to generalize the idea behind the example. Referring to Fig. 5, the dominating regions of tp_i, tp_j, and tp_k have the same area. This indicates that they have the same filtering power. Among them, tp_i and tp_j are very close to each other. Therefore, most of their dominating regions are overlapping. Whereas tp_k is far from tp_j, and thus, its dominating region is less overlapping with that of tp_j than that of tp_i.

Intuitively, the closer two points are, the more similar filtering power they have. Therefore, we measure the filtering power similarity of two points in terms of the distance between them. To avoid selecting two points with similar dominating regions (and thus, similar filtering power), we take into account the distance between every two points to be selected. Given a specific distance threshold Δ, if $dist(tp_1, tp_2) \leq \Delta$ holds, we regard that tp_1 and tp_2 have almost the same filtering capacity. As a result, we select only one of them as a filtering point.

It is noteworthy that this improvement can be applied to both heuristics presented in Section 4.2.1. The improved version of the basic heuristic MaxDist, called *MaxDist2* for short, is shown in Algorithm 6, where the distance check is conducted at line 6.

Algorithm 6: `maxDist2(`SK_{init}`,` K`,` Δ`)`

Input: SK_{init} is the initial skyline;
K is the number of filtering points needed;
Δ is the distance threshold;
Output: a set of multiple filtering points;

1 $F_{flt} = \emptyset$;
2 Pick s_i and s_j from SK_{init} satisfying $|s_i, s_j| \geq |s_{i'}, s_{j'}|$, $\forall\ 1 \leq s_{i'}, s_{j'} \leq l$;
3 $F_{flt} = \{s_i, s_j\}$; $SK' = SK_{init} - \{s_i, s_j\}$;
4 **while** $|F_{flt}| < K$ **do**
5 Pick s_i from SK' satisfying $\sum_{s_j \in F_{flt}} |s_i, s_j| \geq \sum_{s_j \in F_{flt}} |s_{i'}, s_j|$, $\forall\ s_{i'} \in SK'$,
6 and $dist(s_i, s_j) > \Delta$;
7 $F_{flt} = F_{flt} \cup \{s_i\}$; $SK' = SK_{init} - \{s_i\}$;
8 **return** F_{flt}

5 Cost-Efficient Use of Dynamic Filtering Points

In Section 4, we simply fix the number of filtering points to K and use it in a system-wide way. In practice, data space and local skyline cardinality can be different from site to site. A fixed number of filtering points for all data sites can cause some problems. For some individual data sites, the number of filtering points can be too large and become overkill. This unfortunately incurs unnecessary data transmission cost because a number of unused filtering points are transferred via the network.

On the other hand, some other sites that have large data spaces and large local skylines may need more filtering points to achieve good filtering effect. As a result, using a fixed number of filtering points on all data sites may be too rigid to shorten the overall query response time.

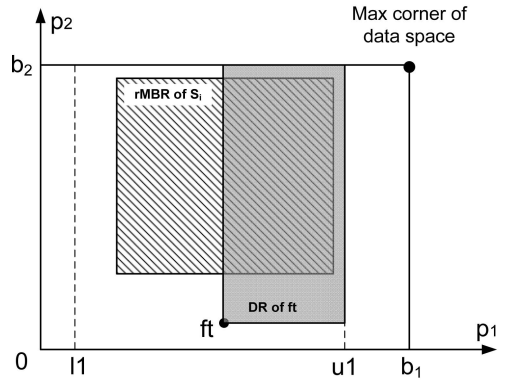

Fig. 6. Example of filtering ratio.

In this section, we propose a cost-efficient model to estimate how many filtering points are adequate for an individual site in terms of filtering power. Based on this model, we accordingly vary the number of filtering points for each site in the process of distributed skyline computation.

5.1 Cost Model

Principally, what we need to do is to ensure that more local skyline points are filtered by K filtering points such that sending all these K filtering points does pay off. In order to evaluate the cost-efficiency of given K filtering points, we first define the concept of *filtering ratio* as follows:

Definition 2. *Given K filtering points, the* filtering ratio *on site S_i, termed as $FR_i(K)$, is the percentage of local skyline points in Sky_i that are filtered by K filtering points:*

$$FR_i(K) = \frac{|FltedSky_i|}{|Sky_i|}. \quad (8)$$

Here, $|Sky_i|$ is the cardinality of local skyline on Site S_i, and $|FltedSky_i|$ is the number of local skyline points filtered by those K filtering points.

With the definition of filtering ratio, we are able to measure the benefit of the K filtering points on a particular site according to the following formula:

$$E_i(K) = FR_i(K) \cdot |Sky_i| - K. \quad (9)$$

To make the K filtering points cost-efficient for a particular data site, we need to ensure $E_i(K) > 0$. As a matter of fact, the larger $E_i(K)$ is, the more benefit we obtain from sending the K filtering points. With this formula, we can find a minimum K that maximizes the benefit of K filtering points for a particular site S_i.

For this purpose, we need to predict $|Sky_i|$ and $FR_i(k)$ in advance for a particular site S_i. Assuming that each site provides data cardinality and distribution, in addition to its MBR, we can estimate the local skyline size $|Sky_i|$ on S_i according to [15], [16], [18], [20]. The relevant result in [16] is used in the experiments.

Regarding $FR_i(K)$, however, it is difficult to directly estimate the number of skyline points on site S_i that can be filtered by K filtering points. Again, we can use the area of fused dominating region of the K filtering points and the data space of site S_i to estimate $FR_i(k)$. Refer to the example shown in Fig. 6. Assuming a uniform data distribution on site S_i, the filtering point ft dominates half of the data space of S_i. Thus, we estimate that ft also dominates half of the local skyline points on S_i. As a result, the estimation of $FR_i(K)$ can be represented as the proportion of intersection area between the fused dominating region of K filtering points and the data space of site S_i, to the whole space.

Without loss of generality, let $f_d = f(\langle d_1, d_2, \ldots, d_n\rangle)$ be the density function for all dimensions, which describes the data distribution. We use $\widetilde{FDR}_{(K)}$ to denote the fused dominating region of K filtering points, and the reduced MBR ($rMBR_i$) to represent the data space of site S_i. The formula to estimate $FR_i(k)$ is given as follows:

$$FR_i(K) \approx f_d \cdot \frac{Area(\widetilde{FDR}_{(K)} \bigcap rMBR_i)}{Area(rMBR_i)}. \quad (10)$$

With the estimations of $|Sky_i|$ and $FR_i(k)$, we propose a greedy algorithm, *MaxFlt* for short. The pseudocode of MaxFlg is shown in Algorithm 7. It basically checks each possible K value that is not larger than the initial skyline cardinality (lines 2-13), and returns the K filtering points that maximize the benefits for a given site S_i (line 14). For each $K(>1)$ value, filtering points are selected according to the improved heuristic MaxDist2 (line 7). Then the filtering ratio and the benefit of those K filtering points are calculated according to formulas defined above (lines 8 and 9). If the benefit is increased since last iteration, the set of filtering points and the benefit are updated (lines 10-12).

Algorithm 7: `maxFlt(`SK_{init}`,` f_d`,` n_i`,` $rMBR_i$`)`

Input: SK_{init} is the initial skyline;
f_d is the density function of S_i;
$rMBR_i$ is the reduced MBR of S_i;
n_i is the number of local skyline tuples of S_i;
Output: a set of multiple filtering points;

```
1  K = 1; maxE_i = 0; maxF_flt = ∅;
2  while K ≤ |SK_init| do
3      F_flt = ∅; E_i = 0;
4      if K == 1 then
5          Pick the one with larger dominating region to F_flt;
6      else
7          F_flt = maxDist2(SK_init, K);
8      FR_i(K) ≈
       f_d · Area(FDR̃_(K) ⋂ rMBR_i)/Area(rMBR_i);
9      E_i = FR_i(K) · n_i − K ;
10     if maxE_i < E_i then
11         maxF_flt = F_flt;
12         maxE_i = E_i;
13     K++;
14 return maxF_flt
```

5.2 Dynamic Update of Multiple Filtering Points

After a site S_i receives a query request with a set of filtering points F_{flt}, it will execute a local query processing. To take advantage of the filtering points, the local processing can be implemented in two ways. In an integrated way, F_{flt} is checked against every candidate point pt met during the skyline computation, any dominated pt is ignored, and any dominated s_i in F_{flt} is removed from the set.

In a separate way, a local skyline is computed first, and then it will be compared with F_{flt} to filter out those unqualified candidates and dominated s_is. The integrated

way is seamlessly applicable to those centralized skyline algorithms that are not based on data transformation [1], [2], [4], [5], [6], whereas the separate way is applicable to all existing skyline algorithms.

For either way, we get a local skyline result SK_i and the reduced set of filtering points F'_{flt}. Note that $F'_{flt} \subseteq F_{flt}$ as some filtering points may be dominated by some local skyline point(s). Before we send the query to further data sites, we need to update F'_{flt} with points in SK_i so that the dominating capability of the multiple filtering points is maintained or increased.

A simple yet efficient way is to treat all points in these two sets equally and select K filtering points from scratch. The heuristics proposed in Section 4.2 can be used to pick fixed K ones from $SK_i \cup F'_{flt}$. To update F'_{flt} based on heuristic MaxSum, SK_i is sorted in nonascending order of fused $\widetilde{VDR}$ values, and merged with F'_{flt} to get the top-K ones as those new filtering points. To update F'_{flt} based on heuristic MaxDist (MaxDist2), Algorithm 5 (Algorithm 6) is adapted to pick K points from $F'_{flt} \cup SK_i$.

Alternatively, we can decide the most appropriate K value and pick K ones from $SK_i \cup F'_{flt}$. For this purpose, the cost model proposed in Section 5.1 can be used for a further site S_i to which the query is sent further.

6 Experimental Study

In this section, we evaluate our distributed skyline query mechanism with extensive experiments. All the simulation experiments are conducted on a Linux Server with two Intel(R) Xeon(TM) 2.80 GHz processors and 1.0 GB RAM. We use two kinds of synthetic data sets, i.e., independent and anticorrelated data sets, and a real-life data set of NBA players' statistics (http://databasebasketball.com), which contains 16,644 records of 17 attributes and approximates a correlated data distribution.

In our preliminary work [3], we have studied the performance of algorithm PaDSkyline by comparing it with **Naive** and **Random** approaches. The experimental results demonstrate the superiority of PaDSkyline. Therefore, we do not include the results from the previous work.

In this section, we aim at investigating the technical extensions proposed and evaluating their performance within our PaDSkyline framework. For multiple filtering points selection, we apply the improvement (Section 4.2.2) to the two basic heuristics (Section 4.2.1), and name them **IpvMaxSum** and **IpvMaxDist**, respectively. We further evaluate a new method named **Predict**, which dynamically selects a most beneficial number of filtering points by predicting $|Sky_i|$ and $FR_i(k)$ of the cost-efficient model presented in Section 5. We compare these three methods with two heuristics **MaxSum** and **MaxDist** [3].

The parameters of the experiments are listed in Table 1, and the default parameter values are given in bold. Same as the results presented in previous experimental study [3], the proposed methods yield similar performance tendency on different data sets. We only detail the results on independent data set for ease of presentation in this paper.

We consider the following four performance metrics:

TABLE 1
Parameters Used in Experiments

Parameter	Values
Dimensionality	2, **3**, 4, 5
Number of sites	**1,000**, 2,000, ..., 10,000
Filtering point percentage	10%, 20%, ..., **50%** ..., 90%
Distance threshold ratio δ	10%, 20%, **30%**, ..., 90%
Cardinality of each site	**1,000**
Number of queries	**50**

- **Query Traffic**, which counts the number of data points sent in the network during the query processing.
- **Data Reduction Efficiency**, the efficiency of multiple filtering points in local skyline computation in terms of the data reduction rate DRR [13]. The DRR is the proportion of data points reduced by the filtering points to the points in the unreduced local skyline. It is defined as

$$DRR = \frac{\sum_{i=1,i\neq org}^{m}(|unredSK_i| - |redSK_i| - K_i)}{\sum_{i=1,i\neq org}^{m}|unredSK_i|}, \tag{11}$$

  where K_i is the number of filtering points sent to a processing site, and m is the network size.
- **Response Time**, which records the overall query processing time, from the moment when a query is issued to the moment when the final result is obtained.
- **Precision**, which indicates how much data returned to the query originator are really useful in the final result. The Precision is defined as

$$Precision = \frac{|finalSK|}{\sum_{i=1,i\neq org}^{m}|returnedSK_i|}, \tag{12}$$

  where $|returnedSK_i|$ is the number of skylines returned to the query originator site, m is the network size, and $|finalSK|$ is the number of skylines retrieved from all the returned results.

6.1 Analysis of Distance Threshold Δ

In the first experiment, we analyze the parameter Δ, which is used as a distance threshold to select filtering points in Section 4.2.2. In our enhanced algorithms, IpvMaxSum and IpvMaxDist, Δ is calculated from the following formula:

$$\Delta = \frac{\sum_{k=1}^{|candtFlt_i|-1}\sum_{j=k+1,pt_k,pt_j\in candtFlt_i}^{|candtFlt_i|} dist(pt_k,pt_j)}{|candtFlt_i| \times (|candtFlt_i|-1)/2} \cdot \delta, \tag{13}$$

where $candtFlt_i$ is the set of candidate filtering points in Site S_i and δ ($0 < \delta < 1$) is parameter to control Δ value. In other words, the distance threshold Δ is calculated from a certain percentage (δ) of average distance between every two points in candidate set.

In our algorithms, IpvMaxSum and IpvMaxDist, we utilize distance threshold Δ as a constraint to select K filtering points. In the implementation of the algorithms, we first give an initial value of δ to generate the threshold.

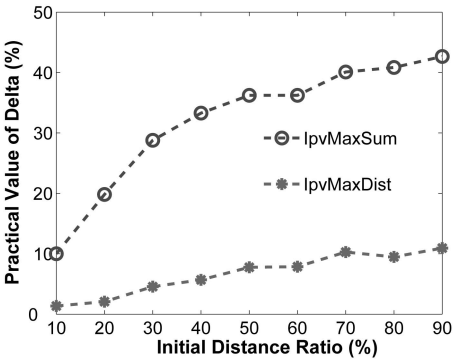

Fig. 7. Practical value of δ for 50 percent filtering points.

However, a large threshold may not produce enough filtering points. Therefore, we may need to automatically adjust δ to guarantee that the preassigned number of filtering points can be selected during the query processing. Consequently, the practical δ value used on the site may be equal to or smaller than the initial one. In this experiment, we show the practical δ value with varying initial distance thresholds.

In Fig. 7, we preassign the percentage of filtering points to be 50 percent and vary δ from 10 to 90 percent. For IpvMaxSum, when $\delta \leq 30\%$, the practical values of δ are equal to the initial ones. When $\delta > 30\%$, the practical value of δ is smaller than the initial one, as we need to relax the constraint of distance threshold to generate more qualified filtering points. All practical values fall into a range of 10 and 42 percent. That is to say, to satisfy the condition of selecting 50 percent filtering points, we must control the δ value into this range. For IpvMaxDist, the practical values are much smaller than the initial ones because it is difficult that a data point has maximum distance to all selected filtering points, and at the same time it has a distance larger than δ to each one of them, if δ is not small enough.

In the next experiment, we evaluate the effect of distance thresholds by varying the initial values, and the results are shown in Fig. 8. The number of filtering points is another parameter for our scheme, which has been studied in previous work [3]; we simply set 50 percent as default value in this paper.

In Fig. 8, both algorithms yield better performance when δ is relatively small, e.g., $\delta < 30\%$. While if δ increases, the performance degrades accordingly. The reason is that when the initial δ goes larger, more points with long distance but small dominating region are added to the filtering points, which decreases the overall filtering capacities. Regarding to IpvMaxSum and IpvMaxDis, there is a trade-off between the size of the dominating regions and the overlapping of dominating regions when we select filtering points. From the results, we can see that IpvMaxSum has better overall filtering capability, which is consistent with the results on basic heuristics, i.e., MaxSum and MaxDist. More detailed comparison results will be presented in the following experiments.

6.2 Comparison of Different Methods

In this section, we demonstrate the results of different methods for performance study, i.e., two basic methods **MaxSum** and **MaxDist**, their improved versions **IpvMaxSum** and **ipvMaxDist**, and **Predict** which can automatically select filtering points according to the cost-efficient model in Section 5. For **IpvMaxSum** and **ipvMaxDist**, we set the initial

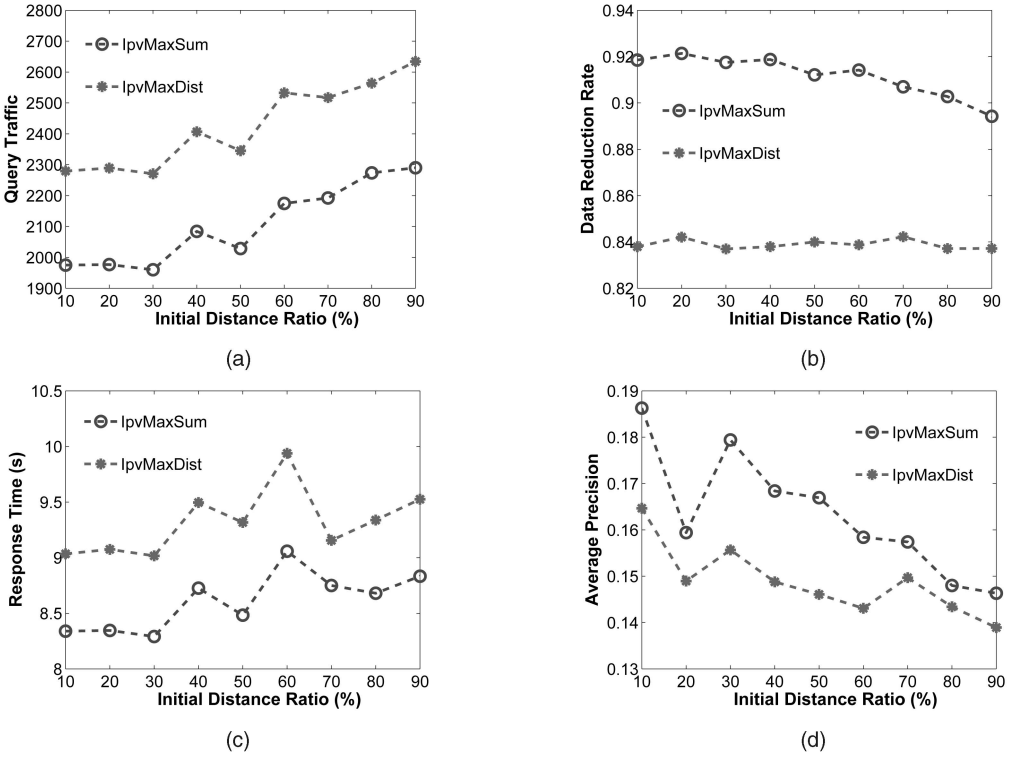

Fig. 8. The effect of initial distance threshold. (a) Query traffic. (b) Data reduction rate. (c) Response time. (d) Precision.

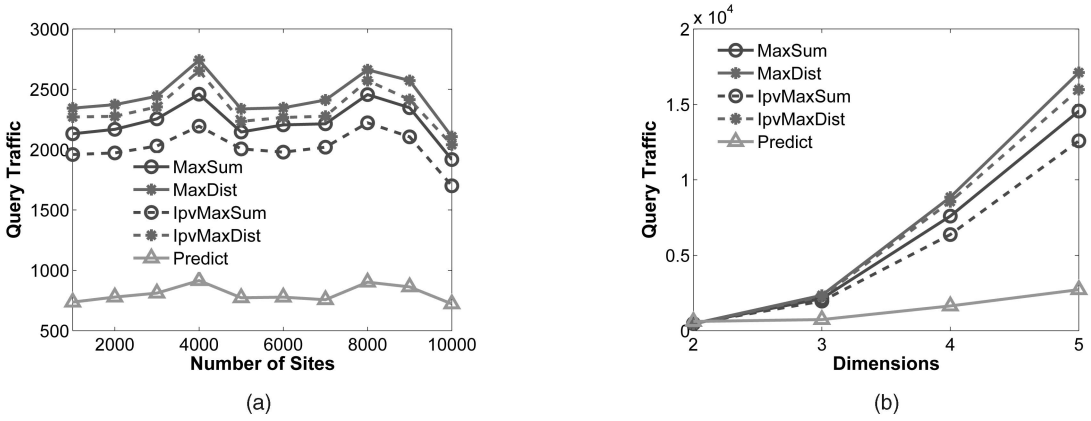

Fig. 9. Performance on query traffic. (a) Network size. (b) Dimensionality.

distance threshold as 30 percent according to our previous experiment, which yields near-optimal performance.

6.2.1 Performance on Query Traffic

We first evaluate the performance of various methods on Query Traffic against two important factors, i.e., network size and dimensionality. In Fig. 9, it is clear that Predict algorithm incurs much less query traffic than other algorithms, due to its dynamical filtering points selection strategy. The Predict method can automatically select "optimal" number of filtering points using the proposed cost model. In our experiments, the "optimal" percentage of filtering points varies from 10 to 60 percent on different sites. We can also see that the improved version can yield better performance, e.g., IpvMaxSum is more efficient than MaxSum, due to the usage of distance threshold Δ, which makes its filtering points more powerful in terms of filtering capability.

6.2.2 Performance on Data Reduction Rate

In this experiment, we measure the performance on data reduction rate (DRR). The higher DRR of an algorithm has, the more unqualified points it filters out. Fig. 10 shows that Predict algorithm again outperforms other algorithms. In Predict, every site utilizes the cost model to select the right filtering points for their next sites, which is expected to cover the next site's data space quite well in an approximate way. This can produce a tailor-made filter set for a specific site with maximized filtering capability, compared with the other methods with preassigned number of filtering points. The sites generally have different data distributions, and therefore, a fixed number cannot be optimal for all the sites in the distributed environment.

6.2.3 Performance on Response Time

We further study the response time of our five algorithms. The response time is calculated at the moment when the query is issued till the final results are retrieved. It includes query propagating time, skyline computing time, filtering point selection time, and result transferring time, etc.

Fig. 11 shows that the performance differences among these algorithms are not significant as that on Query Traffic because the costs of query propagation and local skyline computation are similar for different approaches, and the cost variations of filtering point selection and intermediate data transfer are the main reason of performance difference. The performance of Predict algorithm remains the best because of its effective communication cost reduction, although its automatic filtering point generation may incur more computational cost. However, such local computational cost overhead on sites is marginal compared with data transmission cost in the network. The IpvMaxSum and IpvMaxDist are comparable with the original ones, as the reduced data transmission cost can

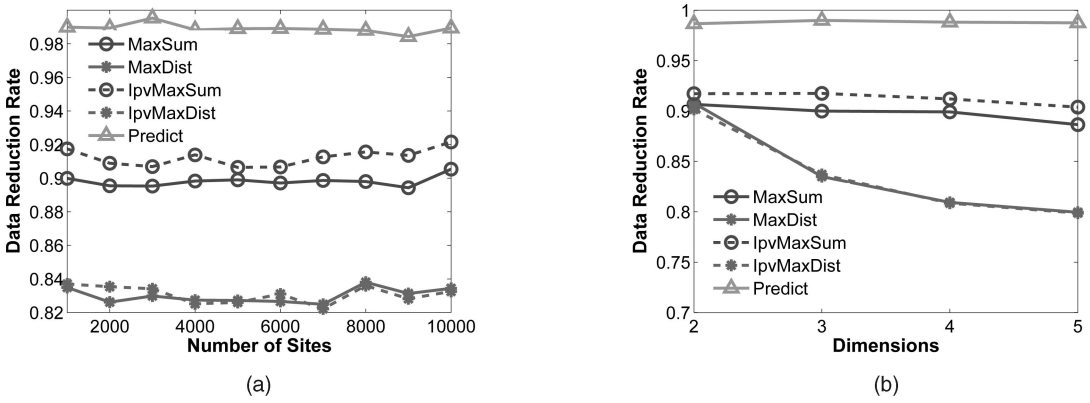

Fig. 10. Performance on data reduction rate. (a) Network size. (b) Dimensionality.

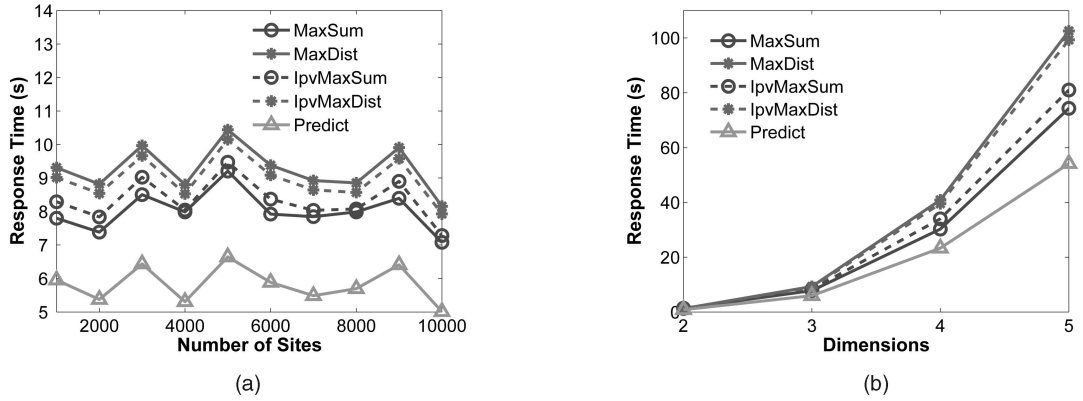

Fig. 11. Performance on response time. (a) Network size. (b) Dimensionality.

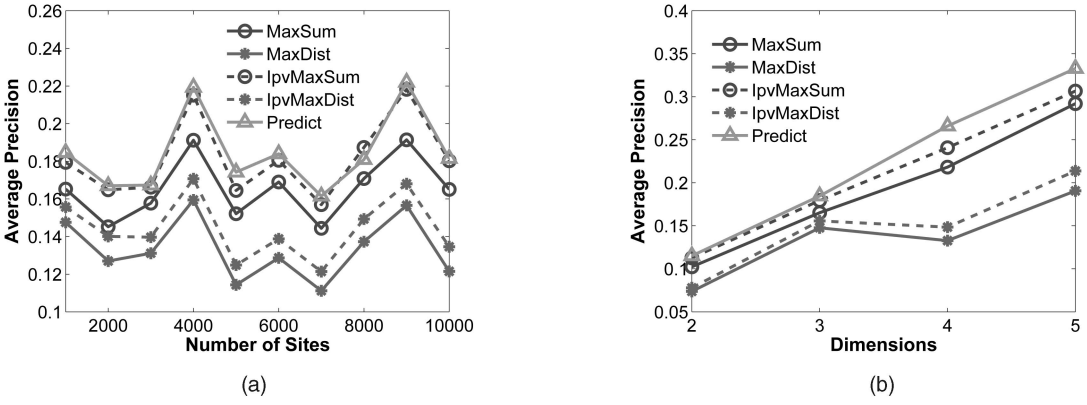

Fig. 12. Performance on average precision. (a) Network size. (b) Dimensionality.

well offset the additional distance evaluating processes on filtering point selection.

6.2.4 Performance on Average Precision

In the last experiment, we study the performance of average precision of the returned results to the query issuers. Fig. 12 shows that the Predict algorithm performs the best among all competitors, due to its powerful filtering capability and high data reduction rate, which prevents more unqualified points from being transferred to the query issuer. The gap here is not significant as the result on DRR because the metric Precision only counts the effectiveness of final results rather than the intermediate results transferred among sites. The improved versions yield better performance than original MaxDist and MaxSum, respectively. Although they deploy the same number of filtering points for skyline processing, the filtering points are more effective with the enhancement of distance threshold.

7 Conclusion

In this paper, we have addressed the problem of constrained skyline query processing against distributed data sites. To accelerate the query processing, we partition all relevant sites into incomparable groups and parallelize the query processing among all groups. We select local skyline points and send them as filtering points together with the query to relevant data sites, in order to prevent more data from being transmitted through the network. Furthermore, a dynamic filtering points selection strategy is proposed based on a novel cost-efficient model. Extensive experimental results demonstrate the efficiency and effectiveness of our proposals in a distributed network environment.

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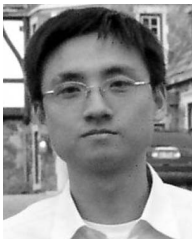

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