Skyline Algorithms on Streams of Multidimendsional Data

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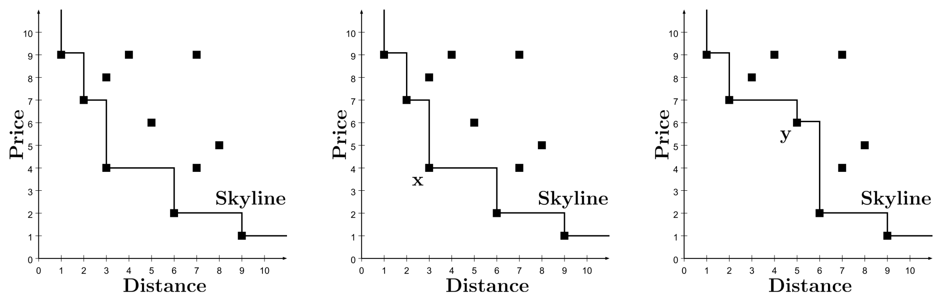
Abstract. We compare three algorithms for skyline processing on streams of multidimensional data with centralized processing, namely, the *Look-Out*, *Lazy* and *Eager* methods, with different dataset types and dimensionalities, data cardinalities and sliding window sizes. Experimental results for time performance and memory consumption are presented. In addition, the problem of computing the exclusive dominance region in higher dimensions is reviewed and a novel correct solution is proposed.

1 Introduction

Skyline queries stem in applications where user preferences determine the result. More formally, if a dominance realtionship in a dataset is defined, a skyline query returns the objects that cannot be dominated by any other object. In other words, if the dataset contains multidimensional objects, an object dominates another one if it is as good in all dimensions, and better in at least one dimension.

Skyline computation algorithms are divided into two categories. The first category consists of algorithms that inspect static data; there are no insertions or deletions while executing the algorithm. For example, a user wants to pick a hotel based on the price and its distance from the beach. The user defines in the dominance relationship that the lower price and the smaller distance, the better. In 1a, the X-axis depicts the distance from the beach, the Y-axis depicts the price, whereas the zigzag line represents the skyline. But hotel rooms are booked by other users and become unavailable, so a mechanism for removing the unavailable rooms, or inserting new ones is needed. This case of skyline computation is called *continuous*, because the skyline is continuously calculated and updated. Figures 1b-1c depict the change of skyline after deleting object x.

Skyline queries have been examined thoroughly in the past. Börzsönyi et al. proposed the use of the skyline operator [1]. Tan et al. used bitmaps and B$^+$-trees to compute the skyline [11]. Kossmann et al. developed an algorithm that enables users to include their preferences at execution time [4]. Chomicki et al. proposed the *SFS* algorithm that uses a monotone function to compute the skyline mainly in relational data [2]. Papadias et al. computed the skyline using the distance from the axis origin with the use of spatial indexing techniques [9].Skyline algorithms on data streams assuming various environments have lastly received increased attention [5]. For example, algorithms for skyline



(a) Static Skyline (b) Skyline at time t=a (c) Skyline at time t=b

Fig. 1: Skyline examples

queries over data streams and centralized processing are: the *LookOut* algorithm [8], *Lazy* and *Eager* algorithms [12]. Also, recent algorithms for skyline queries over data streams and distributed processing are: the *SWSMA* algorithm [15] and the *Two-phase solution* [6].

Even though a lot of work has been done for assorted instances of skyline queries, not much has been done for a rather global and exhaustive evaluation of the skyline algorithms in centralized environments. This paper tries to address these issues by comparing the algorithms for skyline queries over data streams and centralized processing that are widely used: the *LookOut*, *Lazy*, and *Eager* algorithms. In particular, the contribution of this paper lies in:

1. thoroughly evaluating the above skyline algorithms over data streams under several multidimensional datasets, dataset cardinalities and sliding window (SW) sizes
2. explaining the deficiency of the *Lazy* algorithm during the computation of the exclusive dominance region in high dimensions (see Section 2.1), and proposing a solution. This results in an improvement, which makes the algorithms to work more properly and remain efficient for high dimensionalities
3. establishing a simple solution that can be applied in any skyline algorithm over data streams, which uses the exclusive dominance region.

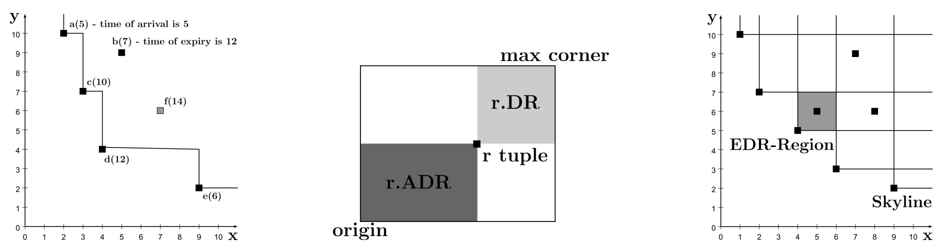
Further insights can be found in the full version of this paper [13].

2 Continuous Skyline Computation Algorithms

Here, we examine the *LookOut* [8], *Lazy* and *Eager* methods [12]. First, certain implementation aspects are examined and then they are evaluated on the basis of execution time, memory allocation and SW size.

2.1 The Lazy Algorithm

The *Lazy* algorithm has been presented by Tao and Papadias in [12]. Changes in skylines may arise if: (i) a new tuple is inserted in the database, or/and (ii) an object expires and has to be removed from the database. The *expiration time* of an object equals *arrival time + sliding window size*. The *Lazy* algorithm uses a pre-processing module (*L-PM*) and a maintenance module (*L-MM*). When a tuple r is inserted, the *L-PM* module checks if it is dominated by a tuple of the current skyline. E.g. in Fig. 2a the arrival of tuple f at time t=14 does not affect the current skyline, because f is dominated by d. Thus, f is saved with the objects not currently used in the skyline, but possibly to be included at a later time. The database which stores the *inactive* data is called *DBrest*, whereas the database which stores the skyline is called *DBsky*.



(a) A new tuple arrives at t=14. The *SW* size is 5.

(b) $r.ADR$ and $r.DR$ regions

(c) *EDR* for a 2-d example

Fig. 2: Skyline algorithms' features

If the incoming object dominates some of the skyline objects, it is stored in *DBsky*, whereas the dominated data are deleted as they will never appear again. The algorithm also defines two regions of a tuple r: (i) the dominance region $r.DR$ with starting point the coordinates of the object r and ending point the maximum coordinates that can appear, and (ii) the anti-dominance region $r.ADR$, which covers a region that spans from the start of the axes to the object itself. Fig. 2b depicts the shape of $r.DR$ and $r.ADR$ in a 2-d setting.

When a tuple arrives, we check if any of the skyline objects are in the $r.ADR$ region. In contrast, the *Lazy* algorithm performs an $r.DR$ query to find the objects belonging in the dominance region of the new tuple. If an object is found in the $r.ADR$ region, then the new tuple is stored in the *DBrest* database, where it will stay until it is included in the skyline or it expires. On the other hand, if there are objects in the $r.DR$ region, they are expunged from the system and the new one is inserted in the skyline. The expiration time for the skyline is set to the lowest value found in it.

The *L-MM* module maintains the data existing in the database already. For this reason, it is executed at the time specified by the *L-PM* module, i.e. when an object expires and has to be deleted from the skyline. The algorithm removes the specific object and removes the objects that are stored in *DBrest* and have expired already. Then the skyline is recomputed, only for the objects that are dominated exclusively by a tuple r, which is about to be deleted. In Fig. 2c the *Exclusive Dominance Region* (*EDR*) for a 2-d example is depicted. Then, the algorithm defines the next execution time for the *L-MM* module, namely the time an object will be deleted from the system.

2.2 The Eager Algorithm

The *Lazy* algorithm has some disadvantages: it stores obsolete data, i.e. tuples that will never be used in the skyline. This motivated its authors to consider the *Eager* algorithm [12], which aims to: (i) lower the memory consumption by keeping only the tuples that are or will be part of the skyline, and (ii) lower the cost of the maintenance module, in this case the *E-MM*. *Eager* achieves these two goals by doing more in the pre-processing module *E-PM*, where the *influence time* is computed to predict at arrival time, if a tuple will be included in a future skyline. If there is no such time, the object can safely be discarded. *Eager* uses an *Event List*, in which the events are sorted ascending based on the time of their respective events. Such events are the expiration of an object, or the transfer from the database to the skyline. Each tuple that is not part of the skyline but will be in the future, is *marked* and transferred to it at the proper time. Specifically in the *E-PM* module, for each incoming tuple, a query finds the tuples that are dominated by the incoming one. These tuples are then removed from the system. The new r tuple is inserted in the database and the *influence time* is computed by finding all the skyline objects that are in the $r.ADR$ region and then keeping the greatest expiry time. At that time point, tuple r will be transferred from the database to the skyline. If the computed influence time equals the arrival time, then the tuple is directly inserted in the skyline, whereas in the event list is marked with an *EX* value. Otherwise, it is stored in the database with the an *EL* value.

When the time for an event comes, the *E-MM* method is executed. This method is less complicated than its respective in *Lazy* algorithm, because more processing is being done in the *E-PM* module. Thus, if the next event in the list is marked as *EX*, then the tuple is simply removed. Otherwise, the tuple is included in the skyline and a new event is stored in the event list to indicate the tuple expiry time.

3 The LookOut Algorithm

The *LookOut* algorithm connects each object with a time interval for which it is valid [8]. This time interval consists of the arrival time and the expiry time. The skyline can change in two occasions: (i) some skyline data are about to expire, and (ii) new data are inserted in the database.

The *LookOut* algorithm takes advantage of two important observations in hierarchical spatial indexes, e.g. R-trees [3] and quadtrees [10]: (i) if point p dominates all corners of a node n, then p dominates all the objects of the node and its children, and (ii) if all corners of a node n dominate a point p, then all objects and its children dominate that point. With these observations *pruning* of nodes is possible and rejection of new objects is faster. Each new object is inserted in the database and then the expiry time is stored in a min heap. The object is checked if it belongs to the skyline by an *isSkyline* algorithm. If an object must be removed, then all candidates that may replace it in the skyline are computed by a *MINI* algorithm. Final insertion is done only if *isSkyline* returns true.

isSkyline uses BFS, i.e. nodes with the lowest distance are inserted first in the heap. When expanding a node, if the lower left corner does not dominate the arriving tuple, it is rejected. If the upper right corner of a child dominates the new tuple, then the algorithm terminates with negative output and the tuple is not inserted in the skyline. If the node is a leaf, the tuple is compared for domination against all tuples of the leaf. If there is such a leaf, the incoming object is not inserted in the skyline, otherwise it is.

The *MINI* algorithm uses also BFS and a min heap for the distance from the origin to the point coordinates. An object that is about to be deleted is passed as an argument and returns the objects that are dominated by it. In addition, these objects are checked before insertion for domination by others that have already been inserted. According to the *isSkyline* algorithm, if the upper right corner is dominated by the object that is about to be deleted, the node is rejected, otherwise if it is an internal dominated node, it is inserted in the heap. If the node currently checked is a leaf, then the local skyline is computed and stored.

4 Experimentation and Evaluation

4.1 Methodology

For a thorough experimentation we rely on well selected datasets. For this reason three data types have been created, by using the generator of [1], and tested: (i) correlated data, (ii) anti-correlated data, and (iii) independent data. As spatial index we use R-trees [3], [7], which store objects in nodes dynamically generated at insertion time. Every node represents a *Minimum Bounding Rectangle* (MBR) and is created by using the coordinates of the lower-left and upper-right MBR corners. This way, during traversal it is possible to prune insignificant nodes.

The *Branch-and-Bound Skyline* (*BBS*) algorithm was used for all three algorithms [9]. The *BBS* algorithm traverses the tree and expands each node, storing in ascending order the distances from the axes origin. In each iteration, the node with the lowest distance is expanded or discarded. If the node is dominated by the existing skyline, it is rejected, otherwise kept. When the algorithm finds a leaf, it inserts the data in the skyline, because they already have been checked.

4.2 Improvement of Lazy Algorithm

According to the *Lazy* algorithm, the *EDR* must be computed for *L-MM* algorithm to work. This is easily achieved in 2-d datasets. An ascending ordered array is needed for each skyline dimension. Then finding the next value, after the point that is about to be deleted, creates a tuple for the upper-right corner of the *EDR*. The *EDR* region is computed by using the coordinates of the point to be deleted with the coordinates of the upper-right corner. This is depicted in Fig. 3.

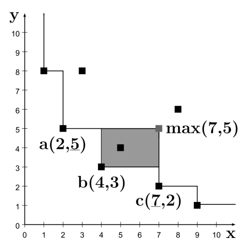


Fig. 3: Computing a 2-*d* EDR

However, in more than 2 dimensions the shape of the *EDR* becomes complicated and its computation hard or even impossible [14]. The authors of [12] do not clarify how the *EDRs* were computed and if the datasets allowed the creation of *EDRs* that could be computed easily as in 2-*d* datasets.

To correct these problems we made an improvement in the Lazy algorithm by replacing the *EDR* computation of a point with its dominance region (*DR*) for dimensions higher than 2. With this technique Lazy can return correct results for all dimensions and remain efficient.

4.3 Time Performance

Several tests were conducted by varying the dimensionality and the *SW* size on an Intel Core 2 Duo P8600, with 3GB RAM, 5400 RPM HDD and 64-bit Windows OS. In all tests the *Eager* algorithm prevails, as tuples are checked only once at arrival time if they belong in the skyline. In addition, the *Eager* algorithm has a linear scaling in all dimensions and *SW* sizes. The *Lazy* algorithm has similar performance for 2-*d* datasets; however, its performance is heavily compromised in higher dimensions. This is due to the dominance region in more than 2 dimensions. In this case, the search region is far greater than in the *EDR* region and, thus, the number of tuples to be checked is much greater as well.

The *LookOut* algorithm is worse in all cases. For small *SW* sizes the difference is comparable, but for sizes greater than some hundreds, the execution time increases dramatically. One reason is the *MINI* algorithm. For *mini-skyline* to be computed, all tuples that have not been pruned in the expansion phase, are potential insertions in the skyline and have to be checked. When the *SW* size gets larger, more tuples are possible members of the skyline and must be checked with each other. Another issue of the *LookOut* algorithm is after the execution of the *MINI*, when the *isSkyline* has to be executed, so that the potential members are sorted and accordingly rejected or inserted in the skyline.

In addition, all three algorithms seem to perform better in correlated data. This is probably due to better MBR creation and more effective pruning, which results in faster tree traversals. Tables 1-3 contain the experimental results.

Dimensions	**2-d**			**4-d**			**6-d**		
SW size	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**
100	16.05	6.17	24.32	14.19	6.49	102.87	29.91	7.09	184.71
1K	7.26	11.01	63.11	122.89	13.29	411.80	139.78	12.49	1264.03
10K	13.09	16.41	189.27	1249.90	30.09	1819.39	11415.70	27.59	9969.60

Table 1: Execution time (in seconds), for anti-correlated data

Dimensions	**2-d**			**4-d**			**6-d**		
SW size	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**
100	5.06	5.44	21.56	14.18	7.56	113.59	25.24	6.72	162.12
1K	6.52	10.89	52.75	123.09	12.93	428.73	137.27	11.79	1231.35
10K	13.99	16.18	184.63	1776.30	31.15	1773.00	12522.34	47.05	12920.20

Table 2: Execution time (in seconds), for independent data

Dimensions	**2-d**			**4-d**			**6-d**		
SW size	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**	**Lazy**	**Eager**	**LookOut**
100	5.28	4.74	18.45	12.20	5.76	86.32	17.96	6.00	151.75
1K	5.48	9.03	45.29	103.70	11.62	323.01	117.59	10.93	1083.14
10K	7.12	14.85	166.96	1118.71	28.10	1624.72	11814.40	38.53	12492.90

Table 3: Execution time (in seconds), for correlated data

4.4 Memory Consumption

Authors of [12] state that *Eager* algorithm was developed to consume less memory than *Lazy*. This is verified by the experiments, because even in the 6-d datasets and the largest *SW*, the algorithm consumes less than 10Mb of memory as shown in Table 4.

On the other hand, the *Lazy* and the *LookOut* algorithms have higher memory consumption, since they exceed in some cases dozens of Mb even in 2-d datasets. The *Lazy* algorithm displays fluctuations in the memory allocation at small *SW* sizes, but its memory consumption is linear in greater sizes. The *LookOut* algorithm has linear consumption, but when the *SW* size is 1M the memory consumption reaches and surpasses 50Mb (see Table 5).

5 Conclusions

This paper examines three skyline algorithms and compares their performance. Experiments established the fact that the dimensionality and the *SW* size are the main factors that affect the performance and the effectiveness of an algorithm, which is not clearly visible in small datasets. Also, the dominance region was used in the *Lazy* algorithm for the computation of the skyline, as the *Exclusive Dominance Region* is sometimes impossible to be computed in higher dimensions.

SW size	2-d	4-d	6-d
100	0.5	0.5	0.5
1K	0.5	0.6	0.6
10K	0.5	0.8	1.2
100K	0.6	1.2	2.9
1M	0.6	1.2	6.9

Table 4: Memory consumption (in Mb) of *Eager* algorithms for 2-, 4-, 6-d data

SW size	Lazy	LookOut
100	10	0.5
1K	2.9	0.6
10K	2.3	1.4
100K	7.5	8.5
1M	67.5	58.0

Table 5: Memory consumption (in Mb) of *LookOut* and *Lazy* for 2-d data

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