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Real-Time Skyline Computation on Data Streams with SLS: Implementation and Experiences

L. Rudenko, M. Endres

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Institut für Informatik
D-86135 Augsburg

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Lena Rudenko, Markus Endres

Institut for Computer Science, University of Augsburg, D-86135 Augsburg, Germany
{lena.rudenko,markus.endres}@informatik.uni-augsburg.de

Abstract. Skyline processing has received considerable attention in the last decade, in particular when filtering the most preferred objects from a multi-dimensional set on contradictory criteria. Most of the work on Skyline computation focus on conventional databases, but stream data analysis becomes a high relevant topic in various academic and business fields. Nowadays, an enormous number of applications require the analysis of time evolving data and therefore the study of continuous query processing has recently attracted the interest of researchers all over the world. In this paper, we propose a novel algorithm called SLS for evaluating Skyline queries over continuous settings, and empirically demonstrate the advantage of this algorithm on artificial and real data. Our algorithm continuously monitors the incoming data and therefore is able to maintain the Skyline incrementally. For this, SLS utilizes the lattice structure a Skyline query constructs and analyzes the Skyline in linear time.

Keywords Streams, Skyline, Preferences, Realtime

1 Introduction

Today, data processed by humans as well as computers is very large, rapidly increasing and often in form of data streams. Users want to analyze this data to extract personalized and customized information in order to learn from this ever-growing amount of data, cp. e.g., [1,2,3]. Many modern applications such as network monitoring, financial analysis, infrastructure manufacturing, sensor networks, meteorological observations, or social networks require query processing over data streams, cp. for example [4,5,6]. Therefore stream data processing is a highly relevant topic today.

A stream is a continuous unbounded flow of data objects made available over time. Due to the continuous and potentially unlimited character of stream data, it needs to be processed sequentially and incrementally. However, queries on streams run continuously over a period of time and return different results as new data arrive. That means, looking on stream data twice is not possible. Hence, analyzing streams can be considered as a difficult and complex task which is in

the focus of current research. Many scientists all over the world try to process and to analyze streams to extract important information from such continuous data flows. Babu and Widom [7], e.g., focus on the problem, how to define and evaluate continuous queries over data streams.

On the other hand, preference queries [8,9,10,11,3] have received considerable attention in the past, due to their use in selecting the most preferred items, especially when the filtering criteria are contradictory. In particular, *Skyline queries* [12,13,14], a subset of preference queries, have been thoroughly studied by the database community to filter high relevant information from a dataset. A *Skyline query*, also known as *Pareto preference query*, selects those objects from a dataset D that are not dominated by any others. An object p having d attributes (dimensions) dominates an object q, if p is better than q in at least one dimension and not worse than q in all other dimensions, for a defined comparison function. This dominance criterion defines a partial order and therefore transitivity holds. The Skyline is the set of points which are not dominated by any other point of D. Without loss of generality, the Skyline with the *min* function for all attributes is used in this paper.

Example 1. Figure 1 presents the Skyline of tweets – short messages from Twitter[1]. Each tweet is represented as a point in the two-dimensional space of *activity status* of a user and the *hashtag*. The first dimension (*activity status*) is represented by the status values {active, non-active, unknown} which are mapped to the scores 0, 1, and 2. The second dimension (*hashtag*) is an element of {#pyeongchang2018, #olympics, #olympia2018, #teamgermany, #others} and is represented with the values $0, \ldots, 4$.

Now, the objective is to find all tweets, which are Pareto optimal w.r.t. the activity status and the hashtag, since we assume that *very active users* using the hashtag *#pyeongchang2018* post the most interesting information on the Olympic winter games in Pyeongchang. Of course, there are also less active users using the same hashtag, or users using, e.g., #olympia2018 for their tweets.

Of interest are all tweets that are not worse than any other tweet in both dimensions w.r.t. to our search preference. Tweet t_4 is dominated by the tweets t_1 and t_2, t_5 by t_1, t_2 and t_3. The tweets t_1, t_2 and t_3, on the other hand, are not dominated by any other tweets and build the *Skyline*.

Algorithms proposed for traditional database Skyline computation, e.g., [15,12,16,14], are not appropriate for continuous data and therefore new techniques should be developed to fulfill the requirements posed by the data stream model. The most important property of data streams is that new objects are continuously appended, and therefore, efficient storage and processing techniques are required to cope with high update rates. Hence, a stream-oriented algorithm should satisfy the following requirements (cp. [2]): 1) fast response time, 2) incremental evaluation, 3) limited number of data access, and 4) in memory storage to avoid expensive disk accesses.

[1] Twitter: `https://twitter.com/`

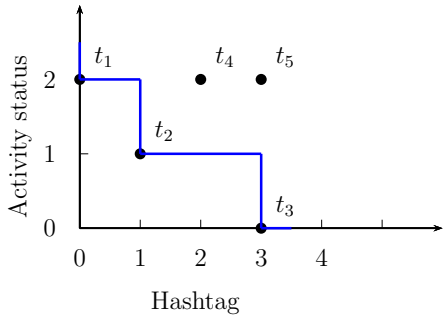


Fig. 1: Skyline on Twitter data.

This paper is an extended version of [17,18] and presents implementation details and comperhensive experiments on the SLS algorithm for *real-time Skyline processing on data streams*. The proposed algorithm is based on the lattice structure representing the better-than relationships that must be built only once for efficient Skyline computation on continuous data. Our algorithm satisfies all four requirements on stream-oriented algorithms as mentioned before.

The remainder of this paper is organized as follows: Section 2 recapitulates essential concepts of Skyline queries. In Section 3, we introduce the *Stream Lattice Skyline* algorithm. Our results on comprehensive experiments are shown in Section 4. Section 5 contains a summary and outlook.

2 Background

2.1 Skyline Queries

The aim of a Skyline query or Pareto preference [3] is to find *the best objects* in a dataset D, denoted by *Sky(D)*. More formally:

Definition 1 (Dominance and Indifference.) *Assume a set of vectors* $D \subseteq \mathbb{R}^d$. *Given* $p = (p_1, ..., p_n), q = (q_1, ..., q_d) \in D$, p dominates q *on* D, *denotes as* $p \prec q$, *if the following holds:*

$$p \prec q \Leftrightarrow \forall i \in \{1, ..., d\} : p_i \leq q_i \wedge \exists j \in \{1, ..., d\} : p_j < q_j \tag{1}$$

Two objects p *and* q *are called* indifferent *on* D, *denoted as* $p \sim q$, *if and only if* $p \not\prec q$ *and* $q \not\prec p$.

Note that following Definition 1 we consider subset of $\mathbb{R}^d$ in that we search fo Skylines w.r.t. the natural order $\leq$ in each dimension.

Definition 2 (Skyline Sky(D).) *The Skyline* Sky(D) *of* D *is defined by the maxima in* D *according to the ordering* $\prec$, *or explicitly by the set*

$$Sky(D) := \{p \in D \mid \nexists q \in D : q \prec p\} \tag{2}$$

In this sense, the minimal values in each domain are preferred and we write $p \prec q$ if p is better than q.

Skylines are not restricted to numerical domains. For any universe Ω and orderings $\prec_i \in (\Omega \times \Omega)(i \in \{1, ..., d\})$ the Skyline w.r.t. $\prec_i$ can be computed, if there exist scoring functions $g_i : \Omega \to \mathbb{R}$ for all $i \in \{1, ..., d\}$ such that $p \prec_i q \Leftrightarrow g_i(p) < g_i(q)$). Then the Skyline of a set $M \subseteq \Omega$ w.r.t. $(\prec_i)_{i=1,...,d}$ is equivalent to the Skyline of $\{(g(p_1), ..., g(p_d)) \mid p_i \in M\}$. That means, categorical domains like *activity status* or *hashtag* as in Example 1 can easily be mapped to a numerical domain.

Note that there is also the concept of top-k Skyline queries where the aim is to find the k best objects [19,20].

2.2 Skyline Queries on Data Streams

Skyline processing on data streams require modified algorithms, since a stream is a continuous dataflow and there is no "final" result after some data of the stream is processed. The result must be calculated and adjusted as soon as new data arrive, since new stream objects received later can build a new Skyline compared with objects already recognized in previously computed (temporary) Skylines. To the best of our knowledge, only *Block-Nested-Loop* (BNL) style algorithms (cp. [12,21,22,23] or [24]) can be adapted to Skyline evaluation on continuous data. These algorithms follow an *object-to-object* comparison approach, an expensive operation with a worst-case runtime of $O(n^2)$, where n is the number of objects.

For analyzing a continuous, unbounded data stream, it is necessary to divide it into a series of (non-overlapping) chunks $c_1, c_2, \ldots$. A BNL-style algorithm would evaluate the Skyline on the first chunk, i.e., $Sky(c_1)$, cp. Definition 2. Since c_2 could contain better objects w.r.t. the dominance criterion in Definition 1, one also has to compare the new objects from c_2 to the current Skyline, i.e., compute

$$Sky(Sky(c_1) \cup c_2) , \tag{3}$$

and so on. However, this leads to a computational overhead if c_2 is large.

3 The Stream Lattice Skyline Algorithm

Our *Stream Lattice Skyline* (SLS) algorithm was developed for efficient real-time Skyline computation on unbounded streams. It does not depend on object comparisons as BNL algorithms do, but on the lattice structure constructed by a Skyline query over low-cardinality domains (either inherently small, such as activity status of a user – or mapped to low-cardinality domains, such as number of followers in Twitter).

3.1 The Idea of SLS

Before we describe our SLS algorithm for real-time stream processing, we revisit the basics of *Hexagon* [25] and *Lattice Skyline* [26] our algorithm is based on.

A Skyline query over discrete domains constructs a *lattice*, a structure where two objects o_1 and o_2 of a dataset have a least upper bound and a greatest lower bound. Visualization of such lattices is often done using *Better-Than-Graphs* (BTG) (similar to Hasse diagrams). An example of a BTG is shown in Figure 2.

The nodes in the BTG represent *equivalence classes*. The idea is to map objects from the stream to these equivalence classes using some kind of feature function. All values in the same class are considered *substitutable*.

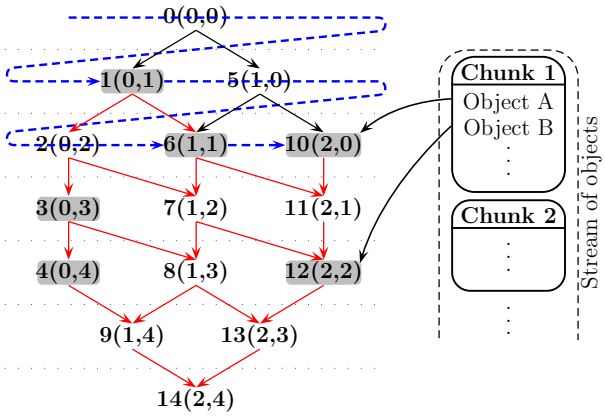


Fig. 2: Stream processing with SLS.

We write [2,4] to describe a two-dimensional domain as well as the maximal possible values of the feature vector representing objects. For example, the BTG in Figure 2 could present a Skyline on the tweets *activity status* of a user ({activ, non-active, unknown}) (values 0, 1, and 2) and the *hashtag* which might be an element of {#pyeongchang2018, #olympics, #olympia2018, #teamdeutschland, #others} (values $0, \ldots, 4$). The arrows in the BTG show dominance relationships between nodes. The node $(0, 0)$ presents the *best node*, whereas $(2, 4)$ is the *worst node*. The bold numbers next to each node are *unique identifiers* (ID) for each node in the BTG. Nodes having the same level are indifferent. That means for example, that neither the objects in the node $(0, 4)$ are better than the objects in $(2, 2)$ nor vice versa. They have the same overall level 4. A dataset does not necessarily contain representatives for each BTG node. All gray nodes are occupied with an element of the data and therefore *non-empty*, white nodes are *empty*.

The elements of the data that compose the Skyline are those in the BTG that have *no path leading to them from another non-empty node*. In Figure 2 these are

the nodes (0,1) and (2,0). All other nodes have direct or transitive edges from these both nodes, and therefore are dominated.

Our approach in general works as follows: After constructing the BTG, which only must be done once, all objects of a chunk are mapped to the corresponding nodes in a consecutive way, e.g., object A is mapped to (2, 0), object B to (2, 2), and so on. Assume all gray nodes in Figure 2 are occupied with data from the first chunk. Afterwards, a *breadth-first traversal* (BFT) runs to find the non-empty nodes (blue dashed line in Figure 2). For the first non-empty node (here $(0, 1)$) we start a *depth-first traversal* (DFT) (red arrows) to mark all transitive dominated nodes as *dominated*. If the DFT reaches the bottom node $(2, 4)$ (or an already dominated node) it will recursively follow all other edges. Thereafter, the BFT continues with node $(1, 0)$, which is empty. The next non-empty node is $(1, 1)$, but dominated. Continue with $(2, 0)$. Since all other nodes are marked as dominated, the remaining nodes, $(0, 1)$ and $(2, 0)$, present the Skyline.

Note that lattice-based algorithms are developed for Skyline computation over low-cardinality domains. An attribute domain $dom(S)$ is said to be low-cardinality if its value is drawn from a set $S = s_1, ..., s_m$, such that the set cardinality m is small. For a low-cardinality domain and $s_i \in \mathbb{R}$, a one-to-one mapping function $f : dom(\mathbb{R}) \to \mathbb{N}_0$, $f(s_i) = i - 1$, can be defined to get discrete values as required in our algorithm.

3.2 The SLS Algorithm

In this section we describe our SLS algorithm in detail. Thereby, we follow the idea depicted in Section 3.1. SLS is based on a series of finite chunks as described in Section 2.2. We divide SLS into three phases:

1. The **Construction Phase** (see pseudo code Phase 1) *initializes the BTG which depends on the Skyline query (see [25,26] for details). This has to be done only once for the first chunk (line 1). For evaluation of the following chunks, the existing BTG will be reused.*
   The BTG is represented by an array (line 2) of Nodes *in main memory. A* Node *is a data structure representing an equivalence class in the BTG, which may contain objects from the stream.* Nodes *are identified by their IDs (cp. [25]), which correspond to their position in the BTG array. A* Node *also contains its status* empty *(initial status),* non-empty*, or* dominated*.*

Phase 1 Construction Phase

```
1: if algorithmFirstRun then
2:     BTG := array of empty Nodes (equivalence classes)
3: end if
```

2. In the **Adding Phase** (see pseudo code Phase 2) we process the input data:
   a. Read the next chunk c_i from the data stream S.

b. Iterate through the objects o_j of chunk c_i (line 3). Each object will be mapped to one node in the BTG. For this we compute the ID *of the current object o_j (line 4) and store it in the BTG array, if the* Node *is not dominated (line 5 and 6).*

Phase 2 Adding Phase

```
1: Input: Next chunk c_i from data stream S
2: ▷ Add objects o_j from chunk c_i to the BTG
3: for o_j in c_i do
4:     ID := compute ID for o_j
5:     if ¬BTG[ID].isDominated() then          ▷ Node is not dominated
6:         BTG[ID].add(o_j)
7:         BTG[ID].setStatus = non-empty
8:     end if
9: end for
```

3. **Removal Phase** (see pseudo code Phase 3): *After all objects in the chunk have been processed, the nodes of the BTG that are marked as* non-empty *and are not reachable by the transitive dominance relationship from any other* non-empty *node of the BTG represent the (temporary) Skyline. From an algorithmic point of view this is done by a combination of* breadth-first traversal (BFT) *and* depth-first traversal *(DFT).*

   We start a BFT at the top of BTG (line 1) and search for the first non-empty *node, which is not dominated. From this node on, we start a DFT to mark dominated nodes (line 4 and procedure DFT in line 9) recursively. When processing objects from the next chunk, this ensures that we do not need to add objects to already dominated nodes in the BTG. This reduces memory requirements and enhances performance. After processing all nodes in the DFT, we continue with the BFT until all nodes are visited. The remaining nodes contain the temporary Skyline set and can be presented to the user.*
4. *Since there is a continuous data stream, Phase 2 and Phase 3 have to be repeated for the next chunks.*

The Skyline computation in Phase 3 can be done after an arbitrary number of processed chunks or after a pre-defined time. Therefore, our algorithm can be used for real-time Skyline evaluation. It is also possible to parallelize this approach in the sense of [27,28]: Parallelize the adding of the objects in the chunk, and, after adding an object, directly start a DFT to mark nodes as dominated.

Since SLS follows the idea of Hexagon and Lattice Skyline, the linear runtime complexity of $\mathcal{O}(dn + dV)$ remains for our algorithm. Thereby, n is the number of input objects, d number of dimensions, and V the size of the lattice, i.e., the product of the cardinalities of the d low-cardinality domains from which the attributes are drawn.

Phase 3 Removal Phase

```
1: Start a BFT beginning at the top of the BTG
2: for each ID in BFT do
3:     if ¬BTG[ID].isDominated() ∧ ¬BTG[ID].isEmpty() then
4:         DFT(ID)              ▷ Start depth-first traversal to mark dominated nodes
5:     end if
6: end for
7:
8: ▷ Start DFT
9: DFT(ID) =
10: for each successor sID of ID do
11:     if BTG[sID].isDominated() then return          ▷ Node is already dominated
12:     end if
13:     ▷ Otherwise remove dominated nodes and continue DFT
14:     BTG[sID].setStatus = dominated
15:     BTG[sID].clear()                                ▷ Set objects to null
16:     DFT(sID)                    ▷ Recursion, continue with successor of sID
17: end for
```

4 Experiments

In this section we present comprehensive experiments on our SLS algorithm.

4.1 Benchmark Framework

In our benchmarks we wanted to explore the behavior of SLS on synthetic and real-world data, depending on the data size, chunk size, and different domain size. For runtime evaluation we compared SLS to the stream variant of BNL, cp. Section 2.2, because to the best of our knowledge, this is the only other stream-based Skyline algorithm.

For our experiments on artificial data we generated correlated (corr), anti-correlated (anti), and independent (ind) data streams as described in [12] and varied three parameters: (1) the data cardinality (n), (2) the data dimensionality (d), and (3) the number of distinct values for each attribute domain.

For real data, we used Twitter records collected over a specific period of time. These objects (tweets) include various attributes such as *name*, *description*, *created_at*, *followers_count*, *status_count*, *lang*, and many more. We mapped all attribute values of theses short messages to a numerical domain according to a mapping function described in Section 3.1.

For analyzing a data stream, it is necessary to divide it into a series of chunks c_i as described in Section 2.2. For this we used Apache Flink[2], an open source platform for scalable stream and batch data processing, which is also able to process real-world data like Twitter. For more details on the implementation of our personalized stream processing framework we refer to [29,30,31].

[2] Apache Flink: `https://flink.apache.org/`

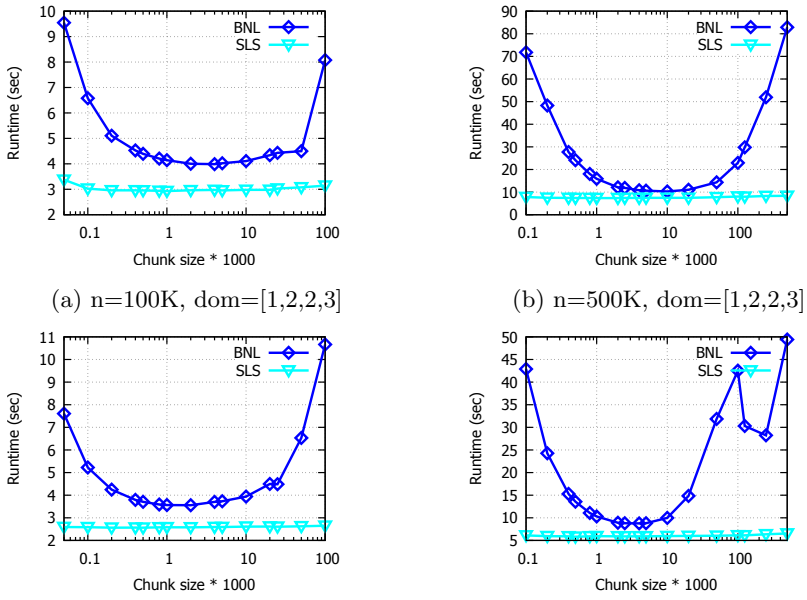
Our algorithms have been implemented using Java 8. All experiments are performed on a single node running Debian Linux 7.1. The machine is equipped with two Intel Xeon 2.53 GHz quad-core processors.

4.2 Influence of the Chunk Size

In our first experiment we varied the chunk size to find out the optimal number of objects per chunk. We also compared BNL to SLS w.r.t. their runtime depending on the chunk size. We used datasets with $100K$ and $500K$ objects and considered the algorithms behaviour for anti-correlated, independent and correlated data distribution.

For a more reliable result we considered different domains: $[1, 2, 2, 3]$, $[1, 5, 10]$, $[1, 2, 2, 2, 2, 2, 2, 2, 3]$, $[2, 3, 7, 8, 4, 10]$, $[1, 5, 2560]$ and $[13, 35, 70]$. Remember, each number corresponds to the maximal possible values of the single domains.

Figure 3 (pages 10 – 11) shows our results for *anti-correlated* data. In all experiments SLS performs significant better than BNL independent of the chunk size. For small chunks (up to 500 objects) and for very large chunks (more than $50K$ objects), BNL is substantial worse than SLS. For small chunk sizes this can be explained by a higher number of unions which has to be carried out after each chunk evaluation, cp. Equation 3. For larger chunks the object comparison process takes more time.



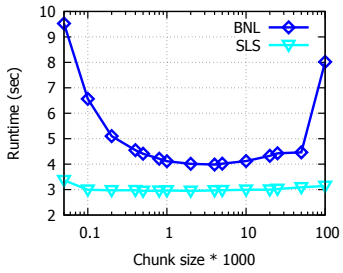
(a) n=100K, dom=[1,2,2,3]

(b) n=500K, dom=[1,2,2,3]

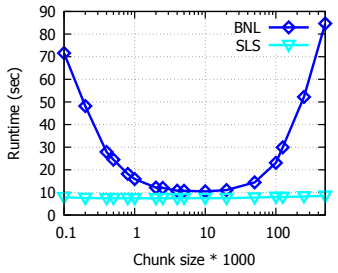
(c) n=100K, dom=[1,5,10]

(d) n=500K, dom=[1,5,10]

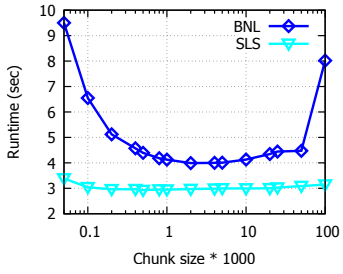
Fig. 3: Influence of the chunk size. SLS vs BNL, anti-correlated data distribution.



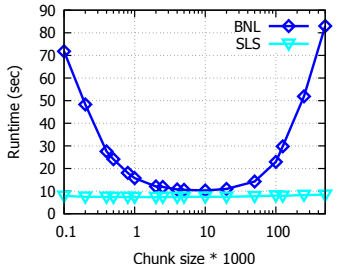
(e) n=100K, dom=[1,2,2,2,2,2,2,2,3]



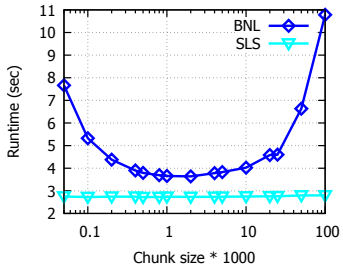
(f) n=500K, dom=[1,2,2,2,2,2,2,2,3]



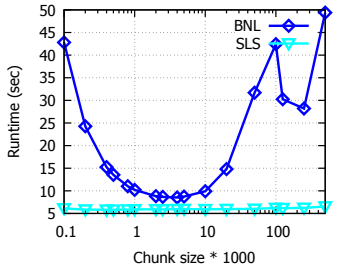
(g) n=100K, dom=[2,3,7,8,4,10]



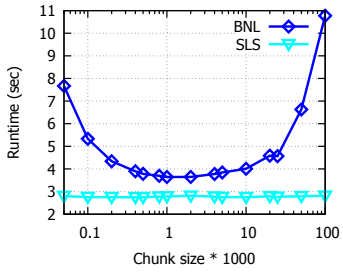
(h) n=500K, dom=[2,3,7,8,4,10]



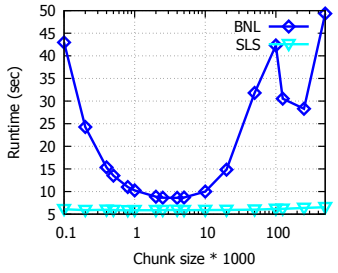
(i) n=100K, dom=[1,5,2560]



(j) n=500K, dom=[1,5,2560]



(k) n=100K, dom=[13,35,70]

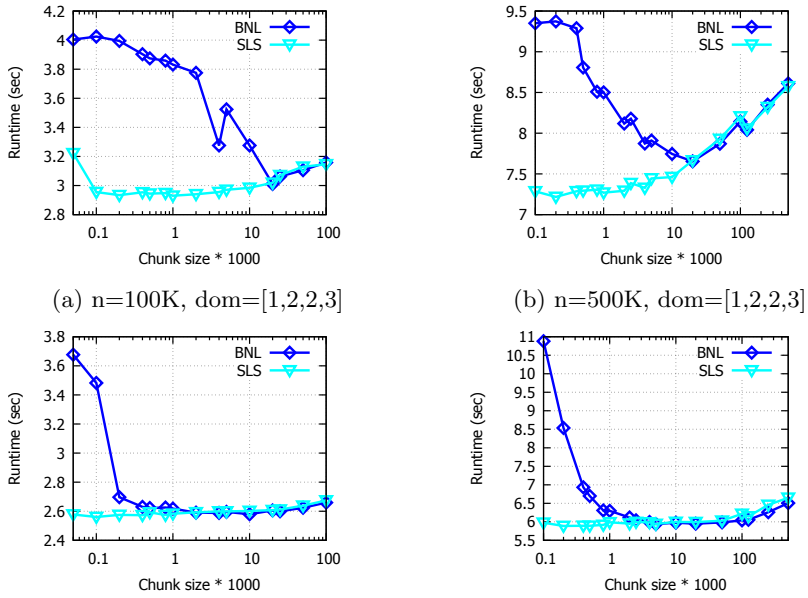


(l) n=500K, dom=[13,35,70]

Fig. 3: Influence of the chunk size. SLS vs BNL, anti-correlated data distribution.

SLS seems to be nearly constant w.r.t. the runtime. However, a closer look to the runtimes of SLS spawns that SLS is slower for small chunks (up to 200 objects) than for chunks with more than 200 objects, cp. **Figures 6a** to **6d** on page 16. This can be explained by the frequent repeating of the BFT and DFT in SLS, which have to be carried out for each chunk. For the chunk size over $20K$ objects the runtime of SLS increases again, because the adding of new objects to the BTG (Phase 2) in SLS is more expensive. In summary, we claim that the optimal chunk size for the best runtime with *anti-correlated* data distribution is between 200 and $20K$ objects.

Figure 4 (pages 12 – 13) presents the comparison result of SLS and BNL for *independent* data distribution. We can see, that SLS has better runtime for small and medium chunks (up to $10K - 20K$ depending on the domains), but for large chunks both algorithms have very similar runtime. For some domains, e.g. [1,5,2560] and [13,35,70] (cp. **Figures 4i** to **4l**) BNL outperforms SLS. In the case of these two domains we are dealing with the high cardinality domains, which produce *deep* BTGs in the sense of the *height*. The required time for the depth search (DFT) in the deep BTG (cp. Removing Phase 3 in Section 3.2) for such domains is significant longer than for low cardinality domains. This enables better runtime of BNL compared to SLS for chunk sizes from $1K$ objects for domains with high cardinality.



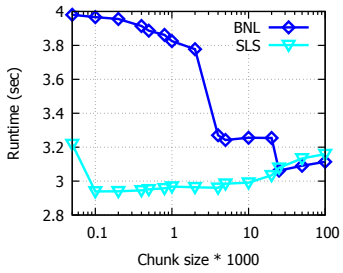
(a) n=100K, dom=[1,2,2,3]

(b) n=500K, dom=[1,2,2,3]

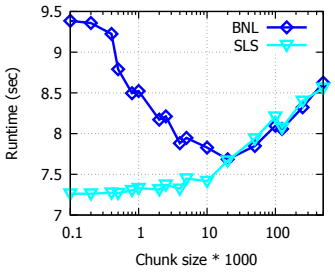
(c) n=100K, dom=[1,5,10]

(d) n=500K, dom=[1,5,10]

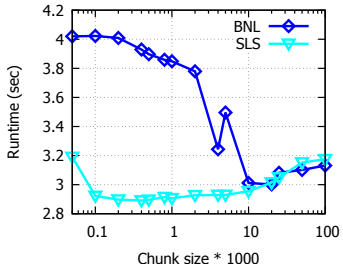
Fig. 4: Influence of the chunk size. SLS vs BNL, independent data distribution.



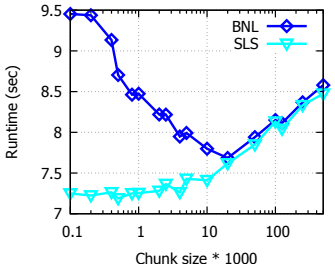
(e) n=100K, dom=[1,2,2,2,2,2,2,2,3]



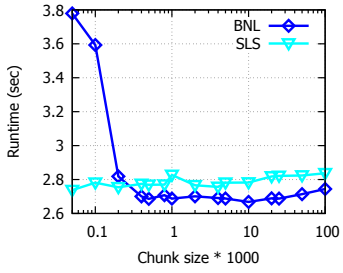
(f) n=500K, dom=[1,2,2,2,2,2,2,2,3]



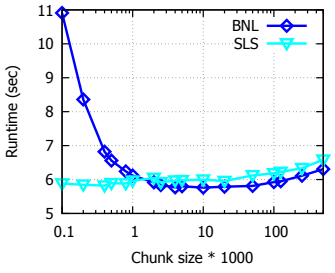
(g) n=100K, dom=[2,3,7,8,4,10]



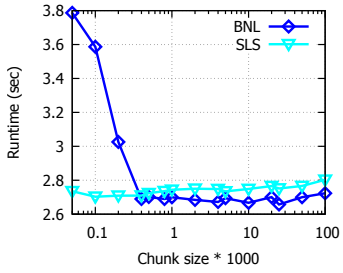
(h) n=500K, dom=[2,3,7,8,4,10]



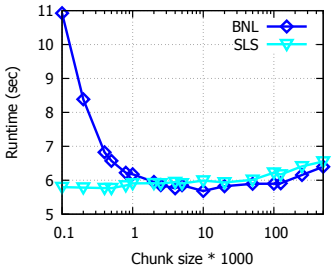
(i) n=100K, dom=[1,5,2560]



(j) n=500K, dom=[1,5,2560]



(k) n=100K, dom=[13,35,70]

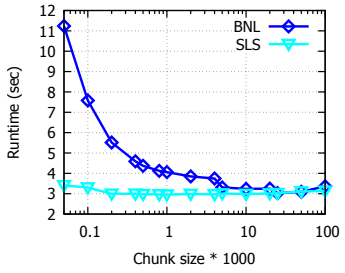


(l) n=500K, dom=[13,35,70]

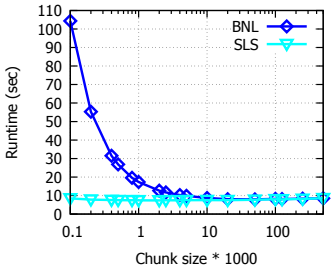
Fig. 4: Influence of the chunk size. SLS vs BNL, independent data distribution.

For a better estimation of the optimal chunk size for *independent* data, we take a closer look to the runtime of SLS. **Figures 6e** to **6h** on page 16 demonstrate the best results for the chunk size between $1K$ and $10K$ objects.

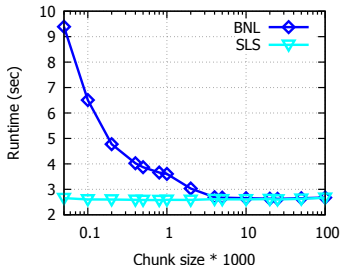
In **Figure 5** (pages 14 – 15) we can observe the runtime comparison of BNL and SLS for *correlated* data. For a chunk size up to $2K$ objects SLS is much better than BNL. For larger chunks both algorithms show very similar runtime.



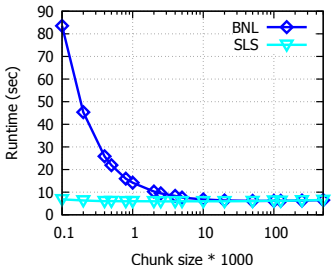
(a) n=100K, dom=[1,2,2,3]



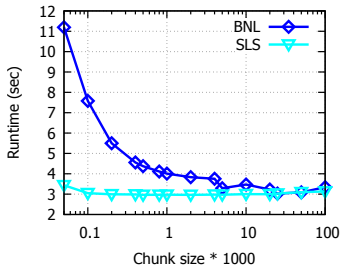
(b) n=500K, dom=[1,2,2,3]



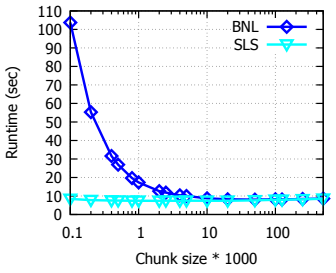
(c) n=100K, dom=[1,5,10]



(d) n=500K, dom=[1,5,10]

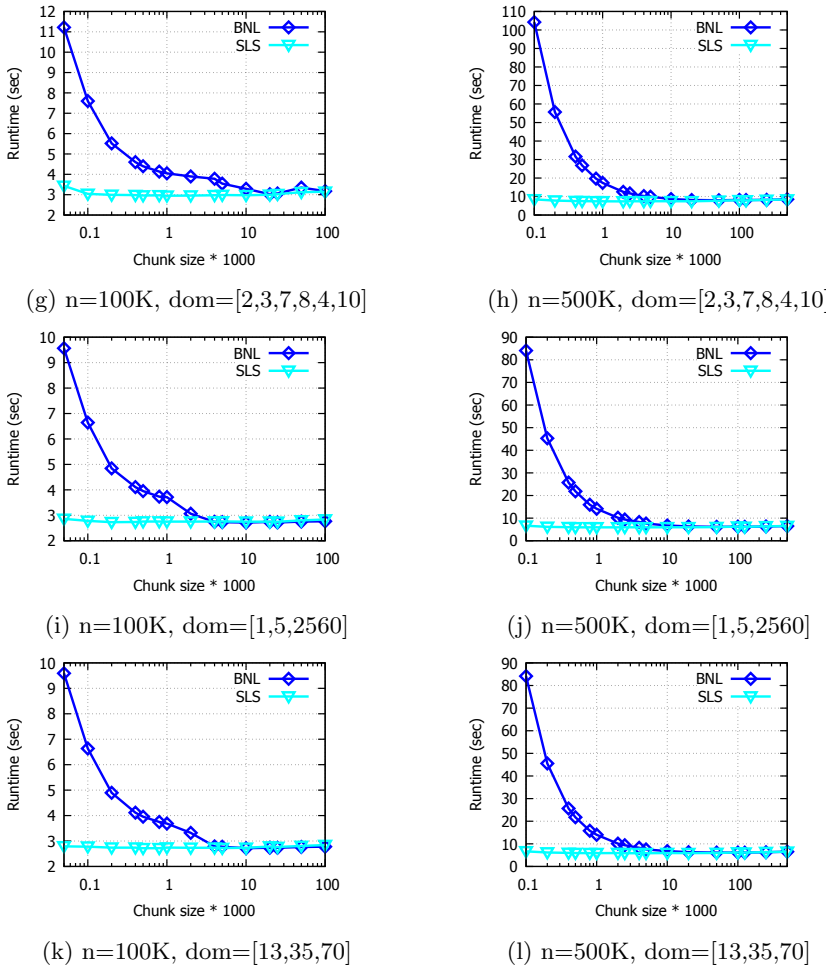


(e) n=100K, dom=[1,2,2,2,2,2,2,2,3]



(f) n=500K, dom=[1,2,2,2,2,2,2,2,3]

Fig. 5: Influence of the chunk size. SLS vs BNL, correlated data distribution.



(g) n=100K, dom=[2,3,7,8,4,10]

(h) n=500K, dom=[2,3,7,8,4,10]

(i) n=100K, dom=[1,5,2560]

(j) n=500K, dom=[1,5,2560]

(k) n=100K, dom=[13,35,70]

(l) n=500K, dom=[13,35,70]

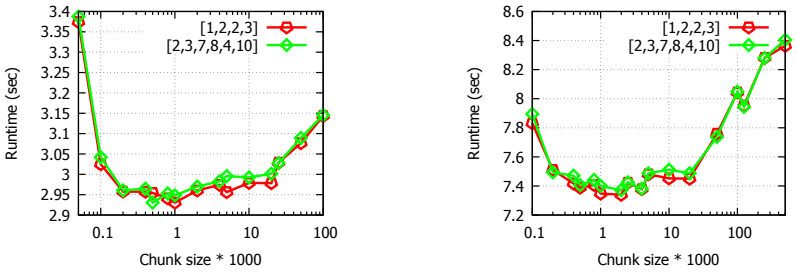
Fig. 5: Influence of the chunk size. SLS vs BNL, correlated data distribution.

As we can see in **Figures 6i** to **6l** on page 17, the SLS achieves its best runtime results for *correlated* data where the chunk size is between 200 and $20K$ objects.

4.3 Influence of Different Domains

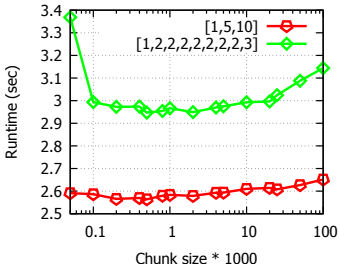
In this experiment, we explored the influence of different domains on SLS. We used data with $10K$ and $500K$ objects.

The results on *anti-correlated* data are shown in **Figure 7** (page 18). In **Figures 7a** and **7b** we varied the number of attributes from 4 to 9, while the domain values remain within the *low-cardinality* range $\{0, ..., 10\}$. The runtime

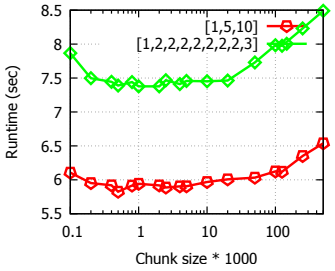


(a) n=100K, anti

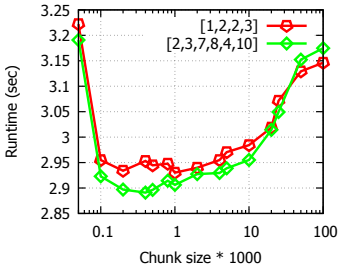
(b) n=500K, anti



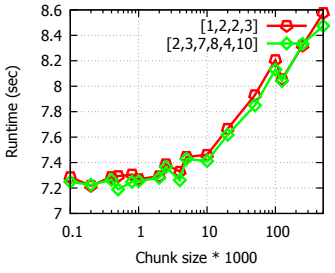
(c) n=100K, anti



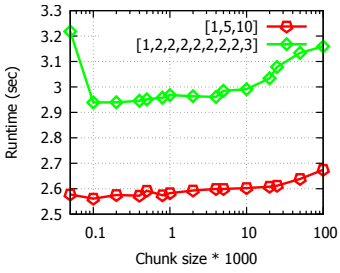
(d) n=500K, anti



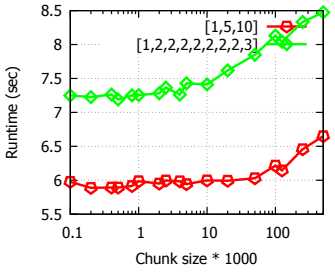
(e) n=100K, ind



(f) n=500K, ind

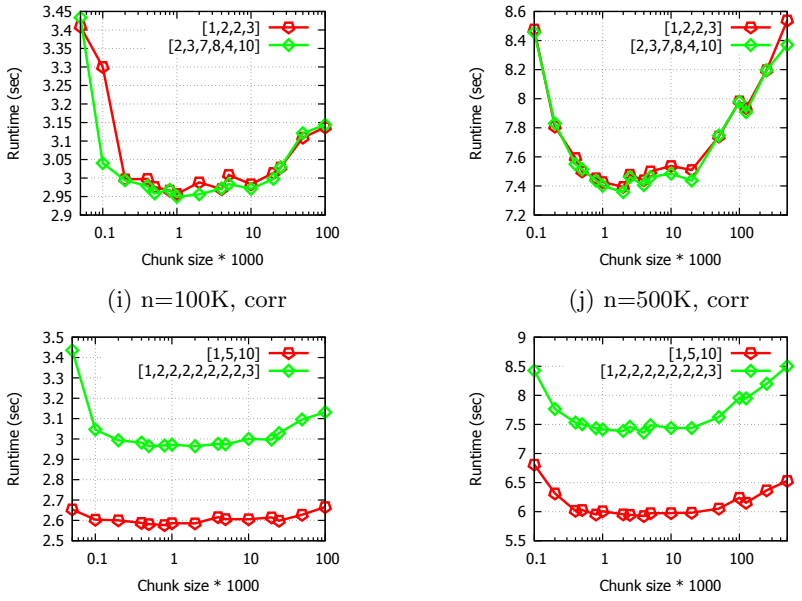


(g) n=100K, ind



(h) n=500K, ind

Fig. 6: Influence of the chunk size on SLS.



(i) n=100K, corr (j) n=500K, corr

(k) n=100K, corr (l) n=500K, corr

Fig. 6: Influence of the chunk size on SLS.

behavior is similar for all domains, because low-cardinality domains produce *flat* BTGs and therefore the runtime for the DFT search in the BTG is nearly constant. Note that the [2,3,7,8,4,10] domain has some $47.5K$ nodes, [1,2,2,2,2,2,2,2,3] produces a BTG with $17.5K$ nodes and [1,2,2,3] has only 72 nodes.

In **Figures 7c**, **7d** and **7e** we compared domains with the same number of attributes, but varied strongly the number of distinct values for each attribute and generated the *high-cardinality* domains. These domains produce *deeper* BTGs in the sense of the *height*, but observe a similar behavior as in **Figure 7a** and **7b**. There are some $36K$ nodes in the largest BTG and only 132 nodes in the smallest.

In **Figure 7f** we compared two domains ([1,2,2,3] and [2,1,2,3,2,1,10,2,2]) producing *flat* BTGs and two domains building *deep* BTGs ([13, 35, 70] and [1,5,2560]). As we can see in this figure, SLS needs more time for *deep* BTGs, because the required time for depth search (DFT) (c.p. Removing Phase 3 in Section 3.2) for *high-cardinality* domains is significant longer than for *low cardinality* domains.

In summary, the runtimes of SLS are nearly independent from the number of attributes and the size of the domain, as long as we have *low-cardinality* domains. The best chunk size for *anti-correlated* data distribution is between 200 and $20K$ objects for all tested domains.

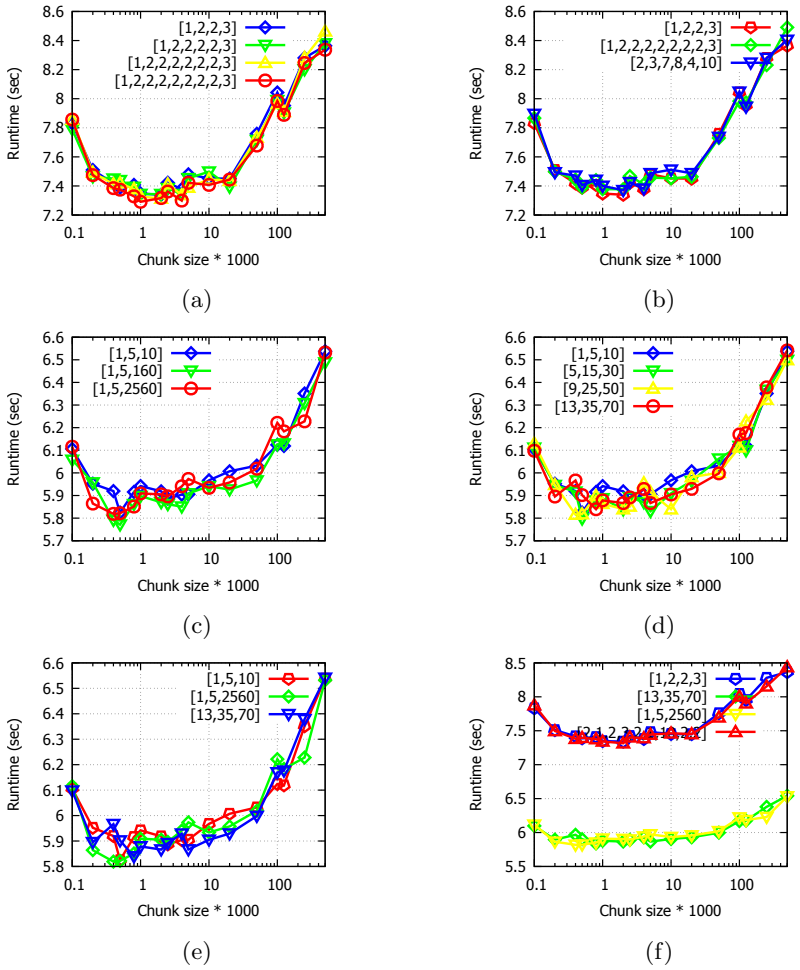


Fig. 7: Influence of different domains, n=500K, anti-correlated data distribution.

The influence of different domains on SLS for *independent* data is shown in **Figure 8** (page 19). Similar to the experiments on *anti-correlated* data, we compared *low-cardinality* domains producing *flat* BTGs in **Figures 8a** and **8b**, *high-cardinality* domains creating *deep* BTGs in **Figures 8c**, **8d** and **8e** and mixed these domains in **Figure 8f**.

The SLS behaviour is very similar for different *low-cardinality* domains and for various *high-cardinality* domains. Furthermore, the runtime of SLS is higher for *deep* BTGs, due to the higher runtime of the DFT.

The best runtime results SLS shows for the chunk sizes up to $10K$ objects. Compared to *anti-correlated* data, the results for *independent* data have no troubles with small chunks. The very large chunks (more than $10K$ objects)

require more runtime because the adding of new objects to the BTG (Phase 2 Section 3.2) in SLS is more expensive.

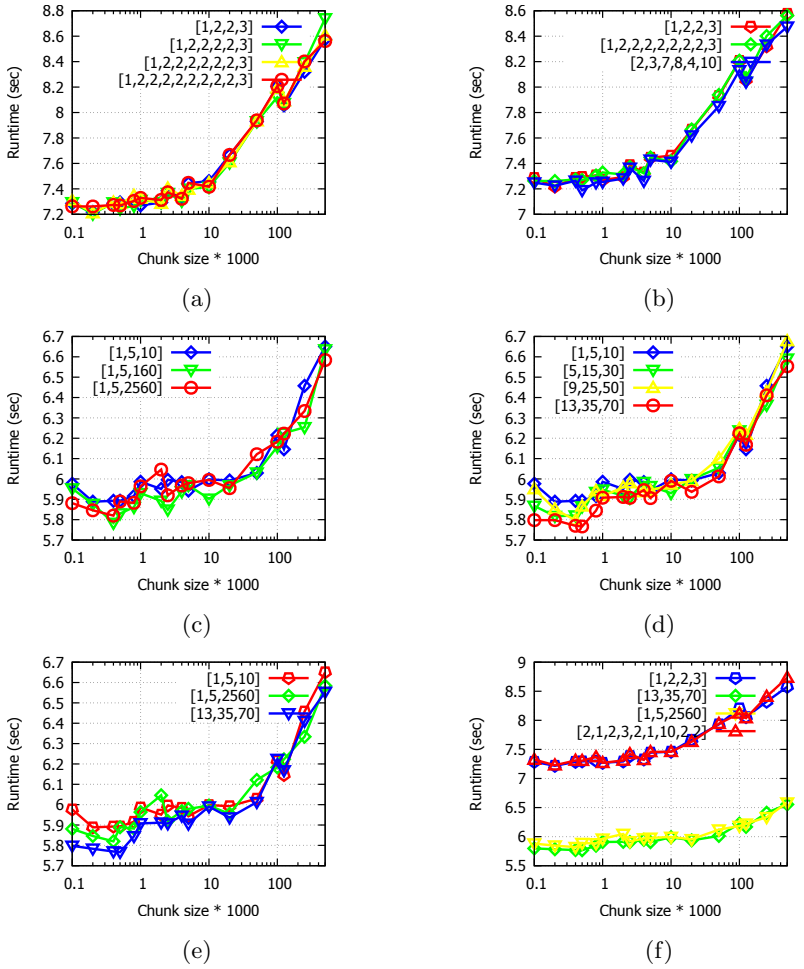


Fig. 8: Influence of different domains, n=500K, independent data distribution.

Figure 9 (on page 20) shows the experimental results for *correlated* data. We used the same domains as for *anti-correlated* and *independent* data and compared *flat* and *deep* BTGs. These results also confirm our assumption: *runtimes of SLS are nearly independent from the number of attributes and the size of the domain, as long as we have low-cardinality domains. Deep* BTGs produced by *high-cardinality* domains are processed by SLS more slowly. The best runtimes were shown for chunk sizes between 200 and $20K$ objects.

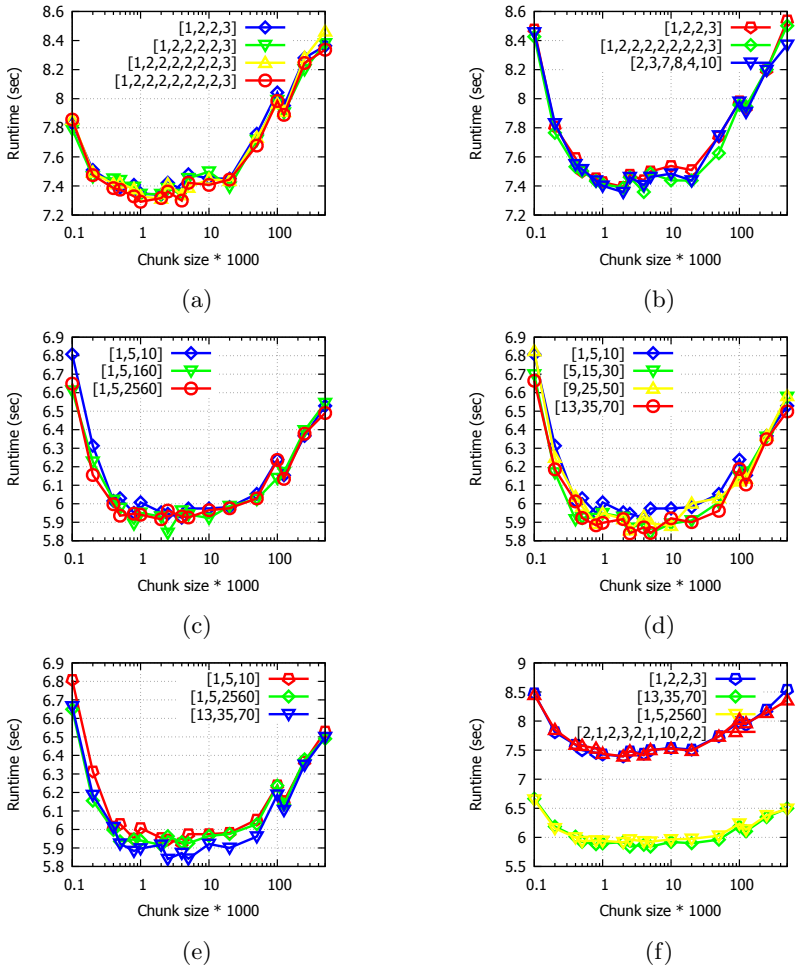
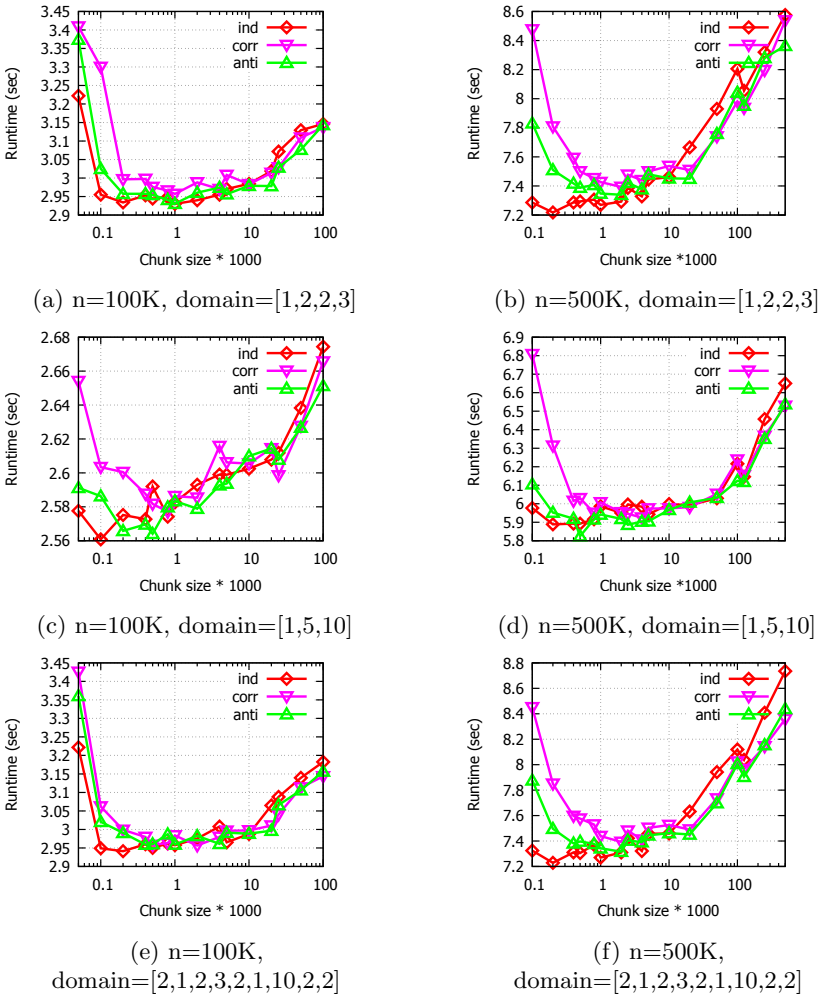


Fig. 9: Influence of different domains, n=500K, correlated data distribution.

4.4 Influence of the Data Distribution

In this experiment we wanted to investigate the impact of different data distributions on SLS. We used independent (ind), correlated (cor), and anti-correlated (anti) data. We varied the size of the dataset ($100K$ and $500K$ objects), and the domains. In **Figure 10** (page 21) we compared *low-cardinality* domains producing *flat* BTGs and in **Figure 11** on page 22 we demonstrated the SLS behaviour for different data distributions with *high-cardinality* domains generating *deep* BTGs.



(a) n=100K, domain=[1,2,2,3]

(b) n=500K, domain=[1,2,2,3]

(c) n=100K, domain=[1,5,10]

(d) n=500K, domain=[1,5,10]

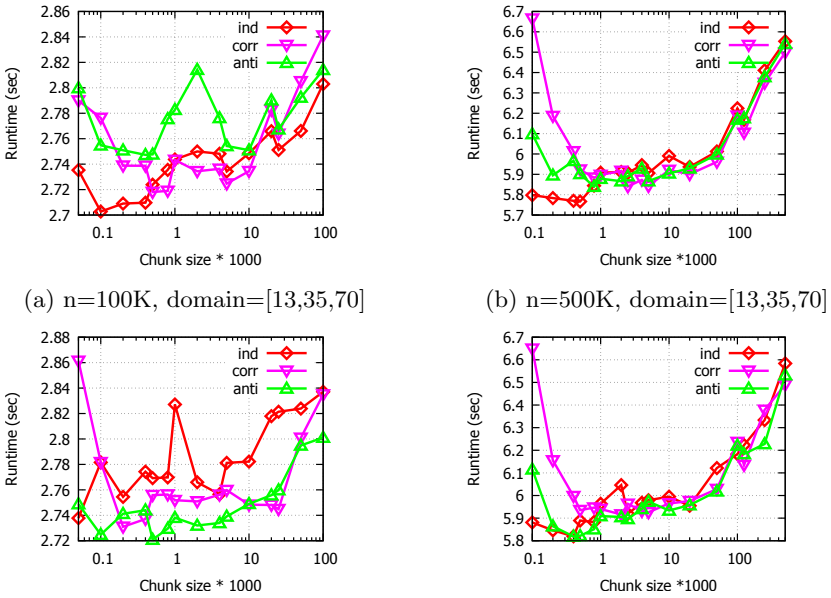
(e) n=100K, domain=[2,1,2,3,2,1,10,2,2]

(f) n=500K, domain=[2,1,2,3,2,1,10,2,2]

Fig. 10: Influence of the data distribution on SLS.

SLS relies on the lattice structure a Skyline query constructs and does not depend on any object-to-object comparisons. Therefore, we expected that the runtime of SLS is nearly the same for any kind of data distribution.

This expectation was completely fulfilled for *low-cardinality* domains as confirmed by **Figure 10**. For *high-cardinality* domains, SLS takes more time for the processing of very small (up to 200 objects) and very large (over $20K$ objects) chunks. We observed the best runtime for the chunks with $[200; 20K]$ objects, as already shown in Section 4.2.



(a) n=100K, domain=[13,35,70]

(b) n=500K, domain=[13,35,70]

(c) n=100K, domain=[1,5,2560]

(d) n=500K, domain=[1,5,2560]

Fig. 11: Influence of the data distribution on SLS.

4.5 Runtime Comparison of SLS, Hexagon and BNL

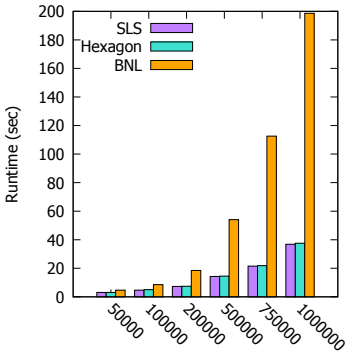
In this section we describe experiments in which we compared SLS with BNL and Hexagon. Since Hexagon is not able to process streams, we analysed the runtimes of Hexagon and compared them to the runtimes of SLS and the stream-based version of BNL with only one big chunk which is equal to the dataset size. We varied the data cardinality, data distribution and domains.

Figure 12 (page 23) presents the result for *anti-correlated* data. In this case SLS clearly outperforms BNL: The larger the dataset, the greater the difference.

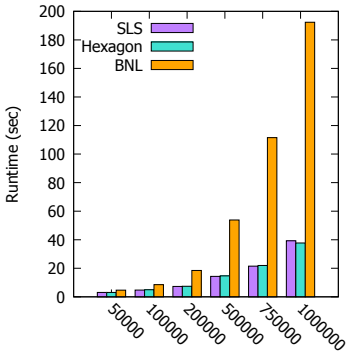
The results for *independent data* are presented in **Figure 13** (page 24). SLS shows often shows the best runtime, but sometimes BNL is better (for example with $50K$ objects for [1,1,2,2,2,2,2,2,2,3] domain or with $500K$ objects for [2856,1,5] domain).

For *correlated* data SLS demonstrates better results for all chunk sizes except $1000K$ objects. For this size BNL is clearly faster (see **Figure 14** on page 25).

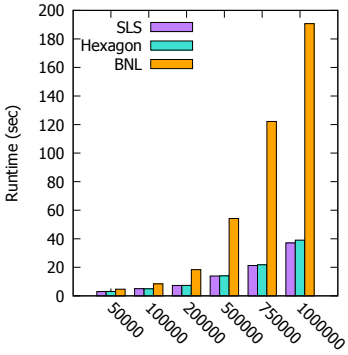
We tested also *Hexagon* in order to find out if our SLS implementation (based on Hexagon) shows very similar runtime results. And indeed, the two algorithms show very similar runtimes how we can see in **Figures 12**, **13** and **14**.



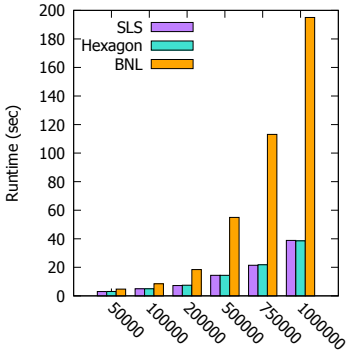
(a) anti, domain=[1,1,2,2,2,2,2,2,2,3]



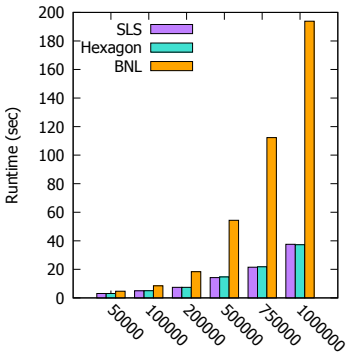
(b) anti, domain=[1,2,2,2,2,3]



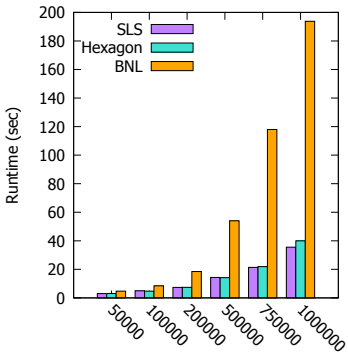
(c) anti, domain=[2,2,100]



(d) anti, domain=[2,3,5,10,100]

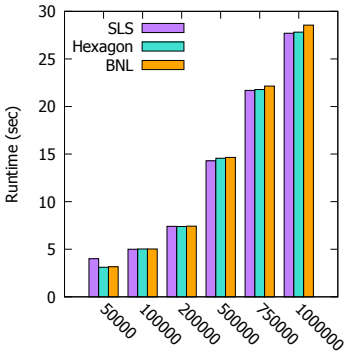


(e) anti, domain=[2856,1,5]

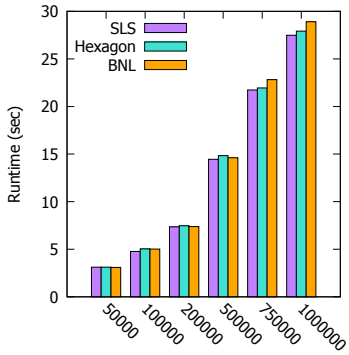


(f) anti, domain=[4,126,77]

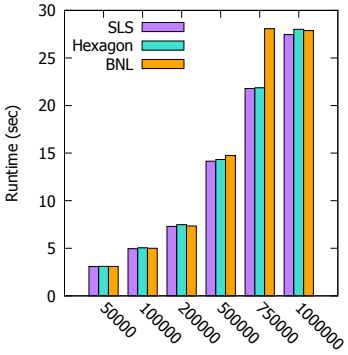
Fig. 12: SLS vs Hexagon vs BNL, anti-correlated data distribution.



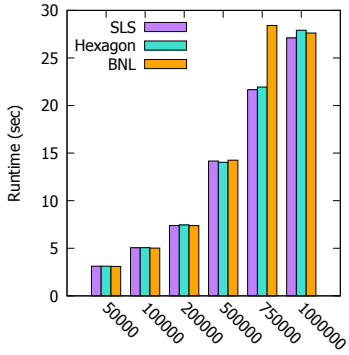
(m) ind, domain=[1,1,2,2,2,2,2,2,2,3]



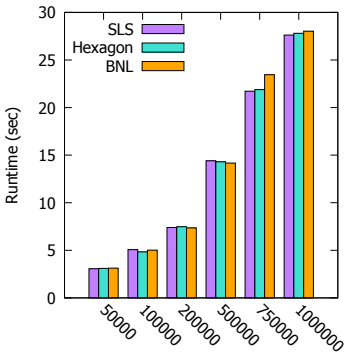
(n) ind, domain=[1,2,2,2,2,3]



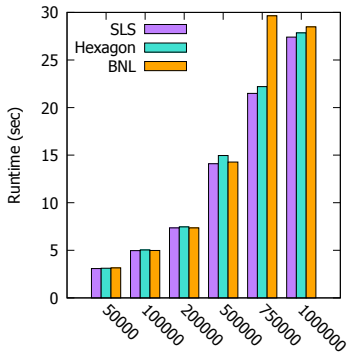
(o) ind, domain=[2,2,100]



(p) ind, domain=[2,3,5,10,100]

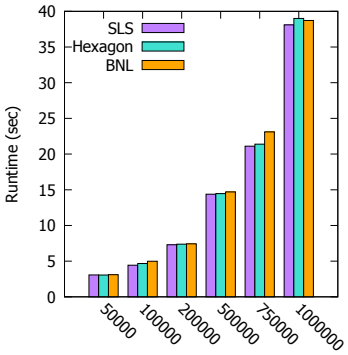


(q) ind, domain=[2856,1,5]

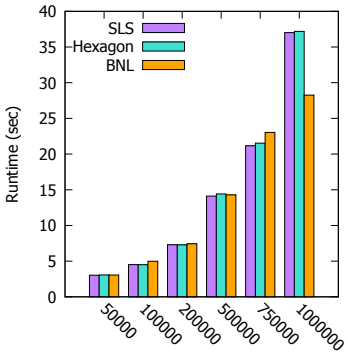


(r) ind, domain=[4,126,77]

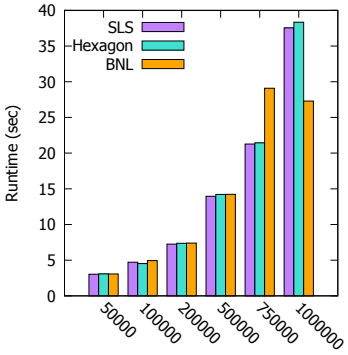
Fig. 13: SLS vs Hexagon vs BNL, independent data distribution.



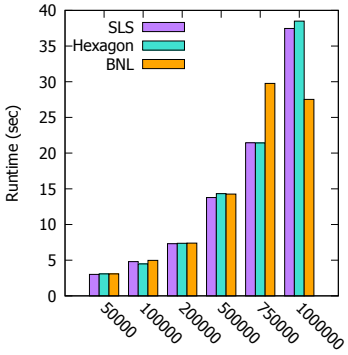
(a) corr, domain=[1,1,2,2,2,2,2,2,2,3]



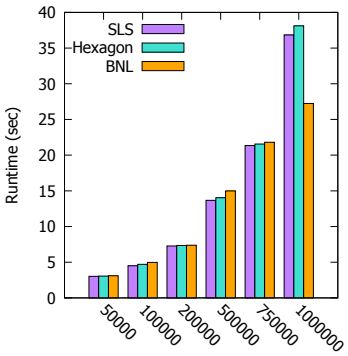
(b) corr, domain=[1,2,2,2,2,3]



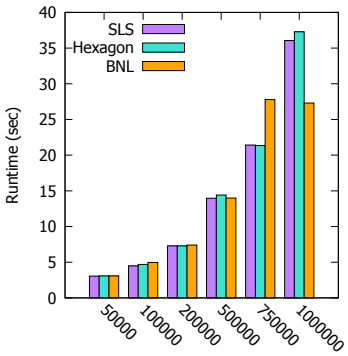
(c) corr, domain=[2,2,100]



(d) corr, domain=[2,3,5,10,100]



(e) corr, domain=[2856,1,5]



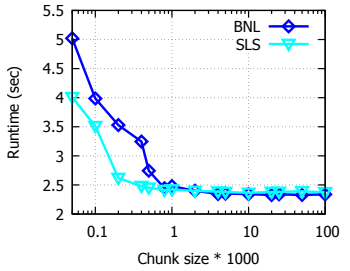
(f) corr, domain=[4,126,77]

Fig. 14: SLS vs Hexagon vs BNL, correlated data distribution.

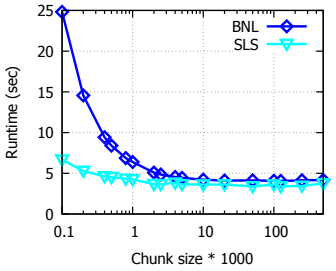
4.6 Real-World Data

For real data experiments we used tweets collected from Twitter over a specific period of time (for repeatable experiments). We used (disjunct) datasets of $100K$ and $500K$ objects. We mapped all attributes to a numerical domain according to a mapping function as described in Section 3.1. For example, we mapped *status_count* (number of posted tweets), *followers_number* and *hashtag* to the numerical domain [2856,5,1].

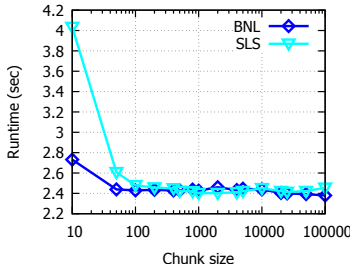
In our first experiment we compared the runtime of SLS and BNL on different data sizes, but the same domain, cp. **Figure 15**.



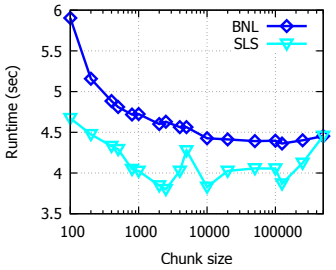
(a) n=100K, domain=[4,126,77]



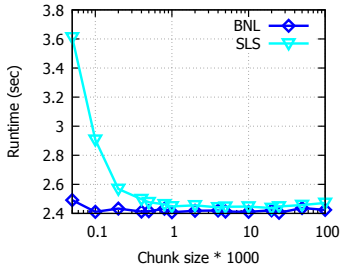
(b) n=500K, domain=[4,126,77]



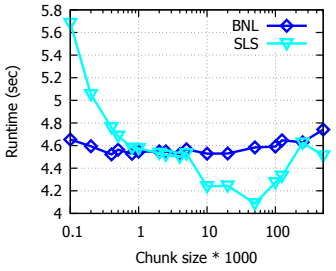
(c) n=100K, domain=[4,77,2,10]



(d) n=500K, domain=[4,77,2,10]



(e) n=100K, domain=[2856,5,1]

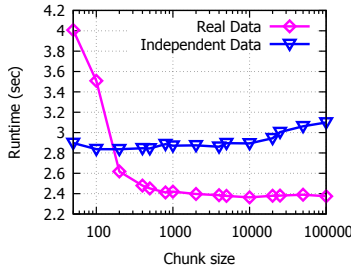


(f) n=500K, domain=[2856,5,1]

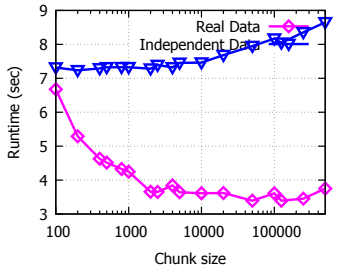
Fig. 15: Performance of SLS vs BNL on real Twitter data.

Again, for BNL the worst runtime is for small chunks due to the frequent repetition of tuple-comparisons in each single chunk. However, for larger chunks, BNL becomes better. We assume that there are some *killer objects* (objects better than most of the other objects in the dataset), which can be accessed earlier by BNL through the larger chunk sizes and therefore speed-ups performance. Nevertheless, SLS is still better than BNL, in particular for the larger dataset.

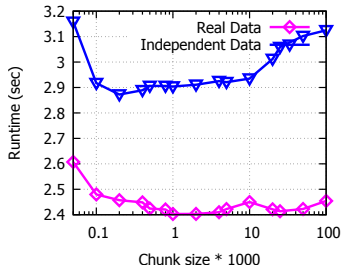
In our second experiment we explored the runtime of SLS for real Twitter data in comparison to generated independent data having the same domains ([4,126,77], [4,77,2,10] and [2856,5,1]). We found it interesting to compare real data to independent generated data, since real data is often assumed to be *independent distributed*. **Figure 16** presents our results.



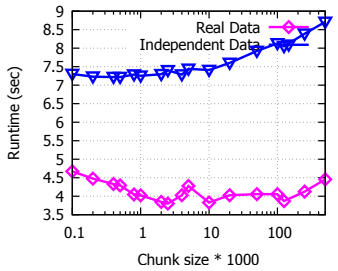
(a) SLS, n=100K, domain=[4,126,77]



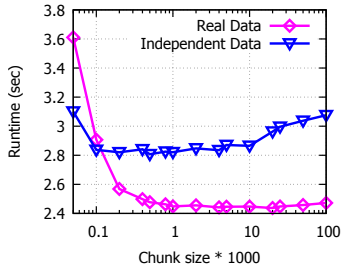
(b) n=500K, domain=[4,126,77]



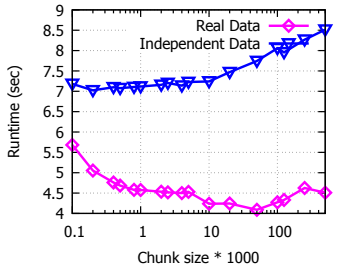
(c) SLS, n=100K, domain=[4,77,2,10]



(d) n=500K, domain=[4,77,2,10]



(e) SLS, n=100K, domain=[2856,5,1]



(f) SLS, n=500K, domain=[2856,5,1]

Fig. 16: Performance of SLS on real and generated independent data.

Since real data is not always perfectly independent distributed and their are some *killer objects* the results show the expected behavior: SLS performs significant better on real data than on artificial data. In addition, we see that also for real data chunk sizes between 200 and $20K$ objects are a good choice.

In summary, we conclude that SLS has an optimal runtime for a chunk size between 200 and $20K$ objects. For this range, SLS outperforms BNL for different domains, dataset sizes, and data distributions for real and synthetic data.

5 Conclusion

There is significant interest of the research community towards continuous query processing. And one information filtering approach on data streams is to compute the *Skyline* set. In this paper, we presented our novel algorithm SLS to find the Skyline on a data stream. Exploiting the lattice, SLS does not rely on object-to-object comparisons like BNL-style approaches, is independent of any data partitioning, and has a linear runtime complexity. In addition, SLS fulfills all requirements on modern stream algorithms: 1) fast runtime as seen in our experiments, 2) incremental evaluation since new chunks can easily be added to the BTG, 3) limited number of data access, because only non-dominated objects are added to the BTG, and 4) in-memory storage since the BTG is hold in RAM to avoid expensive I/O accesses. We also presented comprehensive results on characteristic experiments to confirm that SLS is currently the most advanced real-time Skyline stream processing algorithm.

Nevertheless, there are still open issues which must be addressed in the future. For example, SLS can be parallelized as described in [27,28]. Also we want to enhance our algorithm to handle unrestricted high-cardinality domains as depicted in [32]. However, this could be a challenging task.

Also, maybe index structures could be used for stream data preference processing, cp. [33].

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