

# Probabilistic Skyline Operator over Sliding Windows

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**Abstract**—Skyline computation has many applications including multi-criteria decision making. In this paper, we study the problem of efficient processing of continuous skyline queries over sliding windows on uncertain data elements regarding given probability thresholds. We first characterize what kind of elements we need to keep in our query computation. Then we show the size of dynamically maintained candidate set and the size of skyline. We develop novel, efficient techniques to process a continuous, probabilistic skyline query. Finally, we extend our techniques to the applications where multiple probability thresholds are given or we want to retrieve “top-k” skyline data objects. Our extensive experiments demonstrate that the proposed techniques are very efficient and handle a high-speed data stream in real time.

## I. INTRODUCTION

Uncertain data analysis is an important issue in many emerging important applications, such as sensor networks, trend prediction, moving object management, data cleaning and integration, economic decision making, and market surveillance. In many scenarios of such applications, uncertain data is collected in a streaming fashion. Uncertain streaming data computation has been studied very recently and the existing work mainly focuses on aggregates and top- $k$  queries [8], [14], [28].

Skyline analysis has been shown as a useful tool [3], [7], [21], [24] in multi-criterion decision making. Given a certain data set  $D$ , an object  $s_1 \in D$  dominates another object  $s_2 \in D$  if  $s_1$  is better than  $s_2$  in at least one aspect and not worse than  $s_2$  in all other aspects. The skyline on  $D$  comprises of objects in  $D$  that are not dominated by any other object from  $D$ . Skyline computation against uncertain data has also been studied recently [22]. In this paper, we will investigate the problem of efficient skyline computation over uncertain streaming data where each data element has a probability to occur.

Skyline computation over uncertain streaming data has many applications. For instance, in an on-line shopping system products are evaluated in various aspects such as *price*, *condition* (e.g., brand new, excellent, good, average, etc), and *brand*. In addition, each seller is associated with a “trustability” value which is derived from customers’ feedback on the seller’s product quality, delivery handling, etc. This “trustability” value can also be regarded as occurrence probability of the product since it represents the probability that the product occurs

exactly as described in the advertisement in terms of delivery and quality. A customer may want to select a product, say laptops, according to multi-criteria based ranking, such as low price, good condition, and brand preference. For simplicity we assume the customer prefers ThinkPad T61 only and remove the brand dimension from ranking. Table I lists four qualified results. Both  $L_1$  and  $L_4$  are skyline points,  $L_1$  is better than (dominates)  $L_2$ , and  $L_4$  is better than  $L_3$ . Nevertheless,  $L_1$  is posted long time ago;  $L_4$  is better than (dominates)  $L_3$  but the trustability of the seller of  $L_4$  is low.

TABLE I  
LAPTOP ADVERTISEMENTS.

Product ID	Time	Price	Condition	Trustability
$L_1$	107 days ago	\$ 550	excellent	0.80
$L_2$	5 days ago	\$ 680	excellent	0.90
$L_3$	2 days ago	\$ 530	good	1.00
$L_4$	today	\$ 200	good	0.48

In such applications, customers may want to continuously monitor on-line advertisements by selecting the candidates for the best deal - skyline points. Clearly, we need to “discount” the dominating ability from offers with too low trustability. Moreover, too old offers may not be quite relevant. We model such an on-line selection problem as probabilistic skyline against sliding windows by regarding on-line advertisements as a data stream (see Section II for details).

Such a data stream may have a very high speed. Consider the stock market application where clients may want to on-line monitor good deals (transactions) for a particular stock. A deal is recorded by two aspects (price, volume) where price is the average price per share in the deal and volume is the number of shares. In such applications, customers may want to know the top deals so far, as one of many kinds of statistic information, before making trade decisions. A deal  $a$  is better than another deal  $b$  if  $a$  involves a higher volume and is cheaper (per share) than those of  $b$ , respectively. Nevertheless, recording errors caused by systems or human beings may make unsuccessful deals be recorded successful, and vice versa; consequently each successful deal recorded has a probability to be true. Therefore, a stream of deals may be treated as a stream of uncertain elements and some clients may only want to know “top” deals (skyline) among the most recent  $N$  deals (sliding windows); and we have to take into consideration the uncertainty of each deal. This is another

example of probabilistic skyline against sliding windows.

In this paper we investigate the problem of efficiently processing probabilistic skyline against sliding windows. To the best of our knowledge, there is no similar work existing in the literature in the context of skyline computation over uncertain data streams. In the light of data stream computation, it is highly desirable to develop on-line, efficient, memory based, incremental techniques using small memory. Our contribution may be summarized as follows.

- We characterize the minimum information needed in continuously computing probabilistic skyline against a sliding window.
- We show that the volume of such minimum information is expected to be bounded by logarithmic size in a lower dimensional space regarding a given window size.
- We develop novel, incremental techniques to continuously compute probabilistic skyline over sliding windows.
- We extend our techniques to support multiple pre-given probability thresholds, as well as “top-k” probabilistic skyline.

Besides theoretical guarantee, our extensive experiments demonstrate that the new techniques can support on-line computation against very rapid data streams.

The rest of the paper is organized as follows. In Section II, we formally define the problem of sliding-window skyline computation on uncertain data streams and present background information. Section III and Section IV present our theoretic foundation and techniques for processing probability threshold based sliding window queries. Results of comprehensive performance studies are discussed in Section V. Section VI extends our techniques to top- $k$  skyline, time-based sliding windows, and a data object with multiple instances. Section VII summaries related work and Section VIII concludes the paper.

## II. BACKGROUND

We use  $DS$  to represent a sequence (stream) of data elements in a  $d$ -dimensional numeric space such that each element  $a$  has a probability  $P(a)$  ( $0 < P(a) \leq 1$ ) to occur where  $a.i$  (for  $1 \leq i \leq d$ ) denotes the  $i$ -th dimension value. For two elements  $u$  and  $v$ ,  $u$  dominates  $v$ , denoted by  $u \prec v$ , if  $u.i \leq v.i$  for every  $1 \leq i \leq d$ , and there exists a dimension  $j$  with  $u.j < v.j$ . Given a set of elements, the skyline consists of all points which are not dominated by any other element.

### A. Problem Definition

Given a sequence  $DS$  of uncertain data elements, a possible world  $W$  is a subsequence of  $DS$ . The probability of  $W$  to appear is  $P(W) = \prod_{a \in W} P(a) \times \prod_{a \notin W} (1 - P(a))$ . Let  $\Omega$  be the set of all possible worlds, then  $\sum_{W \in \Omega} P(W) = 1$ .

We use  $SKY(W)$  to denote the set of elements in  $W$  that form the skyline of  $W$ . The probability that an element  $a$  appears in the skylines of the possible worlds is  $P_{sky}(a) = \sum_{a \in SKY(W), W \in \Omega} P(W)$ .  $P_{sky}(a)$  is called the skyline probability of  $a$ . The equation (1) below can be immediately verified.

$$P_{sky}(a) = P(a) \times \prod_{a' \in DS, a' \prec a} (1 - P(a')) \quad (1)$$

In many applications, a data stream  $DS$  is *append-only* [15], [20], [25]; that is, there is no deletion of data element involved. In this paper, we study the skyline computation problem restricted to the append-only data stream model. In a data stream, elements are positioned according to their relative arrival ordering and labelled by integers. Note that the position/label  $\kappa(a)$  means that the element  $a$  arrives  $\kappa(a)$ th in the data stream.

**Problem Statement.** In this paper, we study the problem of efficiently retrieving skyline elements from the most recent  $N$  elements, seen so far, with the skyline probabilities not smaller than a given threshold  $q$  ( $0 < q \leq 1$ ); that is,  $q$ -skyline. Specifically, we will investigate the problem of efficiently processing such a *continuous* query, as well as *ad-hoc* queries with a probability threshold  $q' \geq q$ .

### B. Preliminaries

**Various Dominating Probabilities.** Let  $DS_N$  denote the most recent  $N$  elements. For each element  $a \in DS_N$ , we use  $P_{new}(a)$  to denote the probability that none of the new arrival elements dominates  $a$ ; that is,

$$P_{new}(a) = \prod_{a' \in DS_N, a' \prec a, \kappa(a') > \kappa(a)} (1 - P(a')) \quad (2)$$

Note that  $\kappa(a') > \kappa(a)$  means that  $a'$  arrives after  $a$ . We use  $P_{old}(a)$  to denote the probability that none of the early arrival elements dominates  $a$ ; that is,

$$P_{old}(a) = \prod_{a' \in DS_N, a' \prec a, \kappa(a') < \kappa(a)} (1 - P(a')) \quad (3)$$

The following equation (4) can be immediately verified.

$$P_{sky}(a) = P(a) \times P_{old}(a) \times P_{new}(a). \quad (4)$$

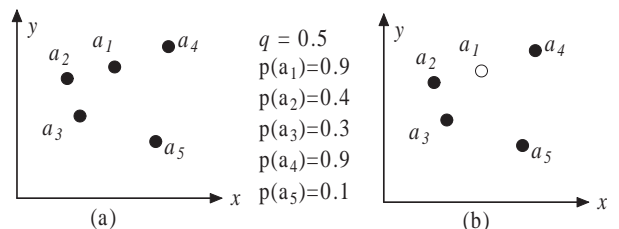


Fig. 1. A Sequence of Data Elements

*Example 1:* Regarding the example in Figure 1(a) where the occurrence probability of each element is as depicted, assume that  $N = 5$ , and elements arrive according to the element subindex order; that is,  $a_1$  arrives first,  $a_2$  arrives second, ..., and  $a_5$  arrives last.  $P_{new}(a_4) = 1 - P(a_5) = 0.9$  and  $P_{old}(a_4) = (1 - P(a_2))(1 - P(a_3))(1 - P(a_1)) = 0.042$ , and  $P_{sky}(a_4) = P(a_4)P_{new}(a_4)P_{old}(a_4) = 0.034$ .  $\square$

**Dominance Relationships.** Our techniques will be based on  $R$ -trees. Below we define various relationships between each pair of entries  $E'$  and  $E$ . We use  $E.min$  to denote the lower-left corner of the minimum bounding box (MBB) of the elements contained by  $E$ , and  $E.max$  to denote the upper-right corner of MBB of the elements contained by  $E$ . Note

that when  $E$  degenerates to a single element  $a$ ,  $E.min = E.max = a$ .

An entry  $E$  fully dominates another entry  $E'$ , denoted by  $E \prec E'$ , if  $E.max \prec E'.min$  or  $E.max = E'.min$  with the property that there is no element in  $E$  allocated at  $E.max$  or there is no element in  $E'$  allocated at  $E'.min$ .  $E$  partially dominates  $E'$  if  $E.min \prec E'.max$  but  $E$  does not fully dominate  $E'$ ; this is denoted by  $E \prec_{partial} E'$ . Otherwise,  $E$  does not dominate  $E'$ , denoted by  $E \prec_{not} E'$ .

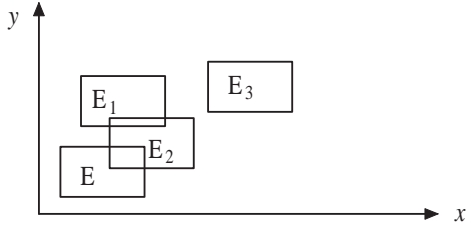


Fig. 2. Dominance relationships.

As depicted in Figure 2,  $E$  fully dominates  $E_3$ , and partially dominates  $E_1$  and  $E_2$ . Note that  $E_1$  does not dominate  $E$  but  $E_2 \prec_{partial} E$ . Clearly, some elements in  $E_1$  may be dominated by elements in  $E$  but elements in  $E$  cannot be dominated by any elements in  $E_1$ . This can be formally stated below which can be verified immediately according to the definitions.

**Theorem 1:** Suppose that  $E \prec_{partial} E'$ . Then some elements in  $E'$  might be dominated by elements in  $E$ . However, if  $E' \prec_{not} E''$ . Then elements in  $E''$  cannot be dominated by any element in  $E'$ .

### III. FRAMEWORK

Given a probability threshold  $q$  and a sliding window with length  $N$ , below in Algorithm 1 is the framework where  $a_{old}$  is the oldest element in current window  $DS_N$  and inserting ( $a_{new}$ ) incrementally computes  $q$ -skyline.

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**Algorithm 1:** Continuous Probabilistic Skyline Computation over a Sliding Window

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1 while a new element  $a_{new}$  arrives do
2   if  $\kappa(a_{new}) \leq N$  then Inserting ( $a_{new}$ );
3   else Expiring ( $a_{old}$ ); Inserting ( $a_{new}$ );
4 end while
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Let  $S_{N,q}$  denote the set of elements from  $DS_N$  with their  $P_{new}$  values not smaller than  $q$ ; that is,

$$S_{N,q} = \{a | a \in DS_N \& P_{new}(a) \geq q\} \quad (5)$$

A critical requirement in data stream computation is to have small memory space and fast computation. In our algorithms, instead of conducting the computation against a whole sliding window ( $N$  elements), we do the computation restricted to  $S_{N,q}$  which will be shown logarithmic in size regarding  $N$  on average. Next, we first show the correctness of restricting the computation to  $S_{N,q}$ .

#### A. Using $S_{N,q}$ Only

In this subsection, we will show the following two things: 1)  $S_{N,q}$  contains all skyline points with  $P_{sky} \geq q$ ; and 2) computing  $P_{sky}$  and  $P_{new}$  against  $S_{N,q}$  will not lead to false positive nor false negative to continuously identify  $S_{N,q}$  and  $SKY_{N,q}$  where  $SKY_{N,q}$  is the solution set; that is, for each element  $a$  in  $SKY_{N,q}$ ,  $P_{sky}(a) \geq q$ .

**No Missing Elements.** The following Lemma is immediate based on (4).

**Lemma 1:** Each  $q$ -skyline point  $a$  (i.e.,  $P_{sky}(a) \geq q$ ) must be in  $S_{N,q}$ .

**No False Hits to Determine  $S_{N,q}$ .** Suppose that  $P_{new}|_{S_{N,q}}(a)$ ,  $P_{old}|_{S_{N,q}}(a)$  and  $P_{sky}|_{S_{N,q}}(a)$  denote  $P_{new}(a)$ ,  $P_{old}(a)$  and  $P_{sky}(a)$  restricted to  $S_{N,q}$ , respectively.

**Example 2:** Regarding the example in Figure 1, suppose that elements  $a_1, a_2, a_3, a_4$ , and  $a_5$  arrive at time 1, 2, 3, 4, and 5, respectively, and  $N = 5, q = 0.5$ . We have that  $S_{N,q} = \{a_2, a_3, a_4, a_5\}$  since values of  $P_{new}$  for  $a_2, a_3$ , and  $a_5$  are the same 1, while  $P_{new}(a_4) = 0.9$  as shown in Example 1. It can be immediately verified that their  $P_{new}$  values restricted to  $S_{N,q}$  remain unchanged. Example 1 also shows that  $P_{old}(a_4) = 0.042$ , while  $P_{old}(a_4)|_{S_{N,q}} = 0.6 \times 0.7 = 0.42$  since  $a_1$  is not contained in  $S_{N,q}$ .  $\square$

Next, we show that for each element  $a$  in  $S_{N,q}$ , calculating  $P_{new}(a)$  against  $S_{N,q}$  is the same as calculating against the whole window  $DS_N$ .

**Theorem 2:** For each element  $a \in S_{N,q}$ ,  $P_{new}|_{S_{N,q}}(a) = P_{new}(a)$ .

Theorem 2 immediately follows from the following Lemma.

**Lemma 2:** For each element  $a \in S_{N,q}$ , if there is an element  $a' \in DS_N$  such that  $a' \prec a$  and  $a'$  is newer than  $a$ , then  $a' \in S_{N,q}$ .

**Proof:** Since  $a' \prec a$  and  $a'$  is newer than  $a$ , each element that is newer than  $a'$  and dominates  $a'$  must dominate  $a$ . Consequently,  $P_{new}(a) \leq P_{new}(a')$ . As  $P_{new}(a) \geq q$ ,  $P_{new}(a') \geq q$ . Thus, the theorem holds.  $\blacksquare$

Note that  $P_{old}$  values against  $S_{N,q}$  are imprecise; nevertheless, below we will show that these will not affect a correct determination of  $SKY_{N,q}$ .

**No False Negative to Determine  $SKY_{N,q}$ .** We show that there is no  $a \in SKY_{N,q}$  such that  $P_{sky}|_{S_{N,q}}(a) < q$ .

**Theorem 3:** For each element  $a \in S_{N,q}$ , if  $P_{old}(a) \times P_{new}(a) \geq q$  then  $P_{old}|_{S_{N,q}}(a) = P_{old}(a)$ .

Theorem 3 immediately follows the following lemma - Lemma 3

**Lemma 3:** For an element  $a'$  such that  $a' \prec a$ ,  $a'$  arrives earlier than  $a$ , and  $P_{old}(a) \times P_{new}(a) \geq q$ , then  $a' \in S_{N,q}$ .

**Proof:** Since  $a' \prec a$ , any element dominating  $a'$  must dominate  $a$ . Consequently,  $P_{new}(a') \geq P_{new}(a) \times P_{old}(a) \geq q$ . Thus,  $a' \in S_{N,q}$ .  $\blacksquare$

Note that  $P_{sky}(a) = P(a)P_{old}(a)P_{new}(a)$  where  $P(a) \leq 1$ . This, together with Lemma 1, Theorems 2 and 3, immediately implies the following corollary.

**Corollary 1:** For each element  $a \in S_{N,q}$ , if  $P_{sky} \geq q$  then  $P_{sky}(a) = P_{sky}|_{S_{N,q}}(a)$ .

Corollary 1 immediately implies there is no false negative; that is, there is no  $a \in SKY_{N,q}$  such that  $P_{sky}|_{S_{N,q}}(a) < q$ .

**No False Positive to Determine  $SKY_{N,q}$ .** We show that there is no  $a \in S_{N,q}$  such that  $P_{sky}|_{S_{N,q}}(a) \geq q$  and  $P_{sky}(a) < q$ .

**Theorem 4:** For each element  $a \in S_{N,q}$ , if  $P_{old}(a) \times P_{new}(a) < q$ , then  $P_{old}|_{S_{N,q}}(a) \times P_{new}|_{S_{N,q}}(a) < q$ .

*Proof:* If every element dominating  $a$  is in  $S_{N,q}$  then  $P_{old}(a)|_{S_{N,q}} \times P_{new}(a)|_{S_{N,q}} = P_{old}(a) \times P_{new}(a) < q$ . The theorem holds.

Suppose that at least one element that dominates  $a$  is not in  $S_{N,q}$ . From Lemma 2, all such elements must be older than  $a$ . Let  $Dom(a)$  denote the set of elements that dominate  $a$  and are not in  $S_{N,q}$ . Suppose that  $a'$  is the youngest element in  $Dom(a)$ . It is clear that all elements, which arrive after  $a'$  and dominate  $a'$ , must be contained by  $S_{N,q}$  since they dominate  $a$  and younger than  $a'$ .

Note that  $P_{new}(a') < q$ . Consequently,  $q > P_{new}(a') \geq P_{old}|_{S_{N,q}}(a) \times P_{new}|_{S_{N,q}}(a)$ . ■

Note that  $P_{sky}(a) = P(a)P_{old}(a)P_{new}(a)$  and  $P(a) \leq 1$ . These, together with Theorems 2, 3, and 4, immediately imply the following corollary.

**Corollary 2:** For each element  $a \in S_{N,q}$ , if  $P_{sky}|_{S_{N,q}}(a) < q$ , then  $P_{sky}(a) < q$ .

Therefore, in our techniques we only need to maintain  $S_{N,q}$ , calculate all probabilities against  $S_{N,q}$ , and select elements  $a$  with  $P_{sky}|_{S_{N,q}}(a) \geq q$ . For notation simplification, in the remaining of the paper,  $P_{sky}|_{S_{N,q}}$ ,  $P_{old}|_{S_{N,q}}$ , and  $P_{new}|_{S_{N,q}}$  are **abbreviated to**  $P_{sky}$ ,  $P_{old}$ ,  $P_{new}$ , respectively if there is no ambiguity.

## B. Estimating sizes of $S_{N,q}$ and $SKY_{N,q}$

**Minimality.** It can be immediately verified that in order to avoid getting a wrong solution,  $S_{N,q}$  is the **minimum** information to be maintained.

**Theorem 5:** Each element  $a$  in the current  $S_{N,q}$  with  $P(a) \times P_{new}(a) < q$  will never become a  $q$ -skyline point; however, there is a data stream such that removing  $a$  away will lead to false positive. Moreover, an  $a \in S_{N,q}$  with  $P(a) \times P_{new}(a) \geq q$  and  $P_{sky} < q$  may become a skyline point if old elements dominating  $e$  expire and newly arriving elements do not dominate  $e$ .

Theorem 5 is quite intuitive and we omit the proof due to space limits. Below we give an example.

**Example 3:** Regarding the example in Figure 1 (a), assume that  $N = 4$ . Considering the first window, there are 4 elements  $a_1, a_2, a_3$ , and  $a_4$ .  $S_{N,q} = \{a_2, a_3, a_4\}$  since  $P_{new}(a_1) = 0.6 \times 0.7 < 0.5$ , while  $P_{new}$  values for  $a_2, a_3, a_4$  are all 1. Note that  $P_{sky}|_{S_{N,q}}(a_4) = 0.378$ ; consequently,  $a_4$  is not a  $q$ -skyline point based on the current window.

Regarding the second window when  $a_1$  expires and  $a_5$  arrives.  $S_{N,q} = \{a_2, a_3, a_4, a_5\}$  where  $P_{new}(a_4) = 0.9$ . Other  $P_{new}$  values are 1,  $P_{sky}(a_3) = P(a_3) = 0.3 < 0.5$ , and  $P_{sky}(a_4) = 0.34 < 0.5$ . If we do not record  $a_3$  and  $a_4$  in  $S_{N,q}$ , then  $P_{sky}(a_4)$  will be calculated as  $(1 - P(a_5))P(a_4) >$

0.5 leading to the false result, because  $P_{sky}(a_4)$  should be  $(1 - P(a_2))(1 - P(a_3))(1 - P(a_5))P(a_4) < 0.5$ .

Assume that  $a_1$  and  $a_2$  expire,  $a_5$  is as illustrated, and  $a_6$  does not dominate  $a_4$ . Regarding the window containing  $a_3, a_4, a_5$ , and  $a_6$ ,  $P_{sky}(a_4) = 0.9 \times (1 - 0.3) \times (1 - 0.1) > 0.5$ ; thus,  $a_4$  is a skyline point. □

**Estimating Sizes.** Next we show that the expected sizes of  $S_{N,q}$  and  $SKY_{N,q}$  are bounded by a logarithmic number regarding  $N$ .

Suppose that  $\chi_{q,i}$  is a random variable such that it takes value 1 if the  $i$ th arrival element is a  $q$ -skyline point; and  $\chi_{q,i}$  takes 0 otherwise. Clearly, the expected size  $E(SKY_{N,q})$  of  $SKY_{N,q}$  is as follows.

$$E(SKY_{N,q}) = E\left(\sum_{i=1}^N \chi_{q,i}\right) = \sum_{i=1}^N P(\chi_{q,i} = 1) \quad (6)$$

Let  $I_N = \{j | 1 \leq j \leq N\}$ . Given a set of  $N$  probability values  $\{P_j | 1 \leq j \leq N \text{ \& } 0 < P_j \leq 1\}$ , let  $P(-w) \triangleq \prod_{j \in W} (1 - P_j)$  where  $W$  is a subset of  $I_N$ . Let  $P(W \prec i)$  denote the probability that the  $i$ th element is dominated and only dominated by the elements in  $\{a_j | j \in W\}$ .

**Theorem 6:** Let  $DS_N$  be a sequence of  $N$  data elements with probabilities  $P_1, P_2, \dots, P_N$ . Then,

$$E(SKY_{N,q}) = \sum_{\forall W, i \notin W, P_i \times P(-W) \geq q} P(W \prec i) \times P_i \times P(-W) \quad (7)$$

Below we show that (7) is bounded by a logarithmic size. Given a  $P_i$ , let  $q_{k,i} \triangleq \max\{P_i \times P(-W) | |W| = k\}$ . Removing the probability value from each data element in  $DS_N$  to make  $DS_N$  be a sequence  $DS_N^c$  of  $N$  certain data elements. Let  $P(DOM_i^k)$  denote the probability that there are exactly  $k$  elements in  $DS_N^c$  dominating an element  $i$ . The following lemma immediately follows from (6). Clearly,  $q_{k,i}$  is monotonically decreasing regarding  $k$ ; that is,  $q_{k',i} \geq q_{k,i}$  if  $k' < k$ . Let  $k_i$  denote the largest integer such that  $q_{k,i} \geq q$  for a given  $q$ .

**Lemma 4:**  $E(SKY_{N,q}) \leq \sum_{i=1}^N \sum_{j=0}^{k_i} P(DOM_i^j) \times q_{j,i}$ .

Let  $P(DOMT_i^k)$  denote the probability that there are at most  $k$  elements dominating the element  $i$ . Clearly,  $P(DOM_i^k) = P(DOMT_i^k) - P(DOMT_i^{k-1})$ .

**Corollary 3:**

$$E(SKY_{N,q}) \leq \sum_{i=1}^N \left( \sum_{j=0}^{k_i-1} P(DOMT_i^j) \times (q_{j,i} - q_{(j+1),i}) \right) + P(DOMT_i^{k_i})q_{k_i,i}. \quad (8)$$

Let  $H_{1,l} = \sum_{i=1}^l \frac{1}{i}$ . The  $d$ -th order harmonic mean (for integers  $d \geq 1$  and  $l \geq 1$ ) is  $H_{d,l} = \sum_{i=1}^l \frac{H_{d-1,i}}{i}$ . The theorem below presents the value of  $P(DOMT_i^k)$ .

**Theorem 7:** For a sequence  $DS_N^c$  of  $N$  certain data points in a  $d$ -dimensional space, suppose that the value distribution of each element on any dimension is the same and independent. Moreover, we assume the values of the data elements in each dimension are distinct. Then,  $P(DOMT_i^k) \leq \frac{k+1}{N} \times (1 + H_{d-1,N} - H_{d-1,k+1})$  when  $d \geq 2$  and  $P(DOMT_i^k) = (k + 1)/N$  when  $d = 1$ .

*Proof:* Without loss of generality, we assume that the data elements in  $DS_N^c$  are sorted on the first dimension. Since the value distribution of each element on any dimension is the same and independent, an element has the equal probability to take  $j$ th position on the first dimension among total  $N$  positions; that is  $\frac{1}{N}$  probability to take  $j$ th position ( $1 \leq j \leq N$ ) on the first dimension. Note that when  $a_i$  takes  $j$ th position, any element takes  $j'$ th position cannot dominate  $a_i$  if  $j' > j$ .

When  $d = 1$ , element  $a_i$  must take the first  $(k+1)$  positions to ensure there are at most  $k$  other elements dominating  $a_i$ . Consequently,  $P(DOMT_i^k) = (k+1)/N$ .

We use mathematic induction to prove the theorem for  $d \geq 2$ . For  $d = 2$ , clearly when  $a_i$  takes the first  $(k+1)$  positions, there are at most  $(k+1)$  other elements dominating  $a_i$ . When  $a_i$  takes a  $j$ th position for  $j > k+1$ , the conditional probability that there must be at most  $k$  elements dominating  $a_i$  is  $\frac{k+1}{j}$  since for each permutation with  $a_i$  at  $j$ th position on the first dimension, the value of  $a_i$  on the second dimension must take one of the  $(k+1)$  smallest value among the  $j$  elements with the  $j$  smallest values on the first dimension. Thus, we have:

$$\begin{aligned} P(DOMT_i^k) &= \frac{(k+1)}{N} + \frac{1}{N} \left( \sum_{j=k+2}^N \frac{k+1}{j} \right) \quad (9) \\ &= \frac{k+1}{N} \times (1 + H_{1,N} - H_{1,k+1}) \end{aligned}$$

Assume that the theorem holds for  $d = l$ . For  $d = l + 1$ , it still holds that when  $a_i$ 's value on the first dimension is allocated at the first  $(k+1)$  positions, then there must be at most  $k$  other elements dominating  $a_i$ . When  $a_i$  takes a  $j$ th position for  $j > k+1$ , the conditional probability that there are at most  $k$  elements dominating  $a_i$  is  $P(DOMT_i^k)_{j,l}$  regarding a  $l$ -dimensional space and  $j$  elements for each permutation with  $a_i$  at  $j$ th position on the first dimension. Based on our assumption,  $P(DOMT_i^k)_{j,l} \leq \frac{k+1}{j} \times (1 + H_{l-1,j} - H_{l-1,k+1})$ ; consequently, the  $P(DOMT_i^k)$  regarding the  $(l+1)$ -dimensional space and  $N$  data elements is:

$$P(DOMT_i^k) \leq \frac{k+1}{N} + \frac{1}{N} \sum_{j=k+2}^N \frac{k+1}{j} \times (1 + H_{l-1,j} - H_{l-1,k+1})$$

Since  $1 \leq H_{l-1,k+1}$ , we have:

$$\begin{aligned} P(DOMT_i^k) &\leq \frac{k+1}{N} + \frac{1}{N} \sum_{j=k+2}^N \frac{k+1}{j} \times (H_{l-1,j}) \\ &= \frac{k+1}{N} (1 + H_{l,N} - H_{l,k+1}) \end{aligned}$$

It can be immediately verified that  $H_{d,N} = O(\ln^d N)$ ; consequently  $P(DOMT_i^k) = O(k \ln^{d-1} N)$ . This together with Theorem 7 and Corollary 3 immediately implies that the expected size of  $SKY_{N,q}$  in a  $d$ -dimensional space is poly-logarithmic regarding  $N$  with order  $(d-1)$ .

**Size of  $S_{N,q}$ .** Elements in the candidate set can be regarded as skyline points in a  $(d+1)$ -space by including the time as an additional dimension since  $P_{new}$  can be regarded as the non-dominance probability in such a  $(d+1)$ -space. We have the following theorem.

**Theorem 8:** In a  $d$ -dimensional space, suppose that the distribution on each dimension, including arriving order are independent. On each dimension, the values of the data items are distinct. Let  $P(skyt_i^j)$  denote the probability that there are at most  $j$  elements in  $DS_N^c$  (remove element probabilities from  $DS_N$ ) dominating the  $i$ th element. Let  $p_{k,i} \triangleq \max\{P(\neg W) \mid |W| = k\}$

$$\begin{aligned} E(SKY_{N,q}) &\leq \sum_{i=1}^N \sum_{j=0}^{k_i-1} P(skyt_i^j) \times (p_{j,i} - p_{(j+1),i}) \quad (10) \\ &\quad + P(skyt_i^{k_i}) p_{k_i,i}. \end{aligned}$$

Note that  $P(skyt_i^{k_i})$  can be estimated in the same way as that in Theorem 7 by replacing  $d$  by  $d+1$ . Therefore, the expected size of  $S_{N,q}$  is poly-logarithmic regarding  $N$  with the order of  $d$ .

#### IV. ALGORITHMS

A trivial execution of Algorithm 1 is to visit each element in  $S_{N,q}$  to update skyline probability when an element inserts or deletes; then choose elements  $a$  from  $S_{N,q}$  with  $P_{sky}(a) \geq q$ . Note a new data element may cause several elements to be deleted from  $S_{N,q}$ , nevertheless, the amortized time complexity is  $O(|S_{N,q}|)$  per element which is poly-logarithmic regarding  $N$  with the order of  $d$  (Section III-B).

In this section, we present novel techniques to efficiently execute Algorithm 1 based on aggregate- $R$  trees with the aim to visit as few elements as possible. We continuously, incrementally maintain  $SKY_{N,q}$  and  $S_{N,q}$ .

The rest of the section is organized as follows. We first present data structures to be used. Then we present our efficient techniques to deal with the arrival of a new element for a given probability threshold. This is followed by our techniques to deal with the expiration of an old element for a given probability threshold. Then, we extend our techniques to deal with applications where multiple probability thresholds are given. Finally, correctness and complexity of our techniques are shown.

##### A. Aggregate $R$ -trees

Since  $SKY_{N,q} \subseteq S_{N,q}$ , we continuously maintain  $SKY_{N,q}$  and  $(S_{N,q} - SKY_{N,q})$  to avoid store a data element twice.

In-memory  $R$ -trees  $R_1$  and  $R_2$  on  $SKY_{N,q}$  and  $(S_{N,q} - SKY_{N,q})$ , respectively will be used and continuously maintained. We aim to conduct an efficient computation. Thus, we develop in-memory aggregate  $R$ -trees based on the following observation.

**Observation.** Regarding the example in Figure 3, assume that  $N = 13$ ,  $q = 0.2$ , the occurrence probabilities are as depicted, and  $DS_N = \{a_i \mid 1 \leq i \leq 13\}$ . Suppose that elements arrive according to the increasing order of elements sub-indexes. It can be immediately verified that  $P_{new}(a_1) < 0.2$ ,  $S_{N,q}$  contains  $a_i$  for  $2 \leq i \leq 13$ , and  $SKY_{N,q}$  contains only the elements in  $R_1$ . Two  $R$ -trees are built: 1)  $R_1$  is built against the elements in  $SKY_{N,q}$ ; and 2)  $R_2$  is built against the elements in  $(S_{N,q} - SKY_{N,q})$ .

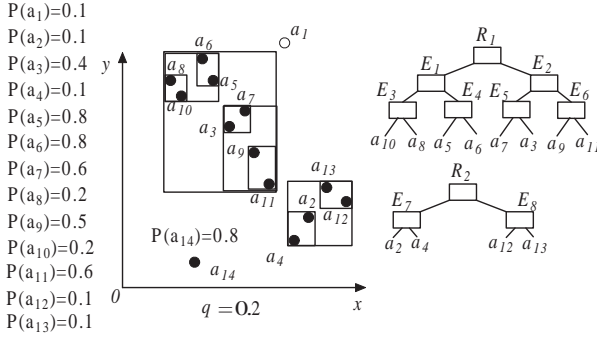


Fig. 3. Aggregate  $R$ -trees

When a new element  $a_{14}$  arrives and  $a_1$  expires. We need to find out the elements which are dominated by  $a_{14}$  and then to determine the elements which need to be removed from  $S_{N,q}$  and  $SKY_{N,q}$ . In fact  $a_{14}$  dominates entries  $E_4$ ,  $E_2$ , and  $R2.root$  (root entry of  $R_2$ ). If we keep the maximum and minimum values of  $P_{new}$  for the elements contained by those entries, respectively, we have a chance not to visit the elements of those entries. Specifically, at an entry if the maximum values of  $P_{new}$  multiplied by  $(1 - P(a_{14}))$  smaller than  $q$ , the entry (i.e. all elements contained) will be removed from  $S_{N,q}$ . On the other hand if the minimum value of  $P_{new}$  multiplied by  $(1 - P(a_{14}))$  is not smaller than  $q$ , then the entry (i.e. all elements contained) remains in  $S_{N,q}$ . Similarly, at each entry we keep the minimum and maximum values of  $P_{sky}$  for the elements contained to possibly terminate the determination of whether elements contained are in  $SKY_{N,q}$ .

Moreover, in this example elements contained by  $E_2$  is in  $S_{N,q}$ , we can update their  $P_{new}$  values globally by keeping a global value  $P_{new}^{global} = P_{new}^{global} \times (1 - P(a_{14}))$  at  $E_2$  to avoid individually update all elements contained in  $E_2$ .

Furthermore, in this example  $a_2$  will be removed from  $S_{N,q}$  once  $a_{14}$  arrives. To avoid update each element contained by  $E_8$  individually due to the removal of  $a_2$ , we can keep a global value  $P_{old}^{global} = P_{old}^{global} \times (1 - P(a_2))$  at  $E_2$  so that we know that the  $P_{old}$  values for elements in  $E_2$  will be updated by multiplying  $\frac{1}{P_{old}^{global}}$ . From time to time, we may remove an entry  $E$  from  $S_{N,q}$  and  $E$  fully dominates another entry  $E'$  which stays in  $S_{N,q}$ . If we keep the no-occurrence probability of the elements in  $E$  -  $P_{noc} = \prod_{a \in E} (1 - P(a))$ , then we can update  $P_{old}^{global}$  at  $E'$  by multiplying  $P_{noc}$ .

**Aggregate Information.** Motivated by the observation above, we maintain  $R_1$  and  $R_2$  as aggregate  $R$ -trees to keep the above information at each entry. We summarize it below.

- At each entry  $E$ , the following information will be stored.  $P_{new}^{global}(E)$  stores the captured multiplication of non-occurrence probabilities of the elements which dominate all elements rooted at  $E$ .  $P_{old}^{global}(E)$  stores the multiplication of non-occurrence probability of the elements that expired and dominate the elements rooted at  $E$ .
- At each entry  $E$ , we use  $P_{noc}(E)$  to store  $\prod_{e \in E} (1 - P(e))$ .
- At each entry  $E$ ,  $P_{sky,min}(E)$  and  $P_{sky,max}(E)$  store the minimum skyline probability and maximum skyline

probability of the elements rooted at  $E$  without including  $P_{old}^{global}$  and  $P_{new}^{global}$  at  $E$ .  $P_{new,min}(E)$  and  $P_{new,max}(E)$  store the minimum and maximum  $P_{new}$  values of the elements rooted at  $E$  without including  $P_{new}^{global}$  at  $E$ .

**Example 4:** Continue the example in Figure 3 against the first 13 elements.

$P_{old}^{global}$  and  $P_{new}^{global}$  at each internal entry are initialized to 1. When  $a_{10}$  arrives, we update  $P_{new}^{global}(E_4)$  from 1 to  $(1 - P(a_{10})) = 0.8$  since  $a_{10}$  dominates the MBB of  $E_4$ , while other  $P_{new}^{global}$  values remain 1.

Here,  $P_{noc}(E_3) = (1 - P(a_{10}))(1 - P(a_8)) = 0.64$ . Similarly, we can calculate values of  $P_{noc}$  at entries  $E_4$ ,  $E_5$ , and  $E_6$ . Then,  $P_{noc}(E_1) = P_{noc}(E_3) \times P_{noc}(E_4)$  and  $P_{noc}(E_2) = P_{noc}(E_5) \times P_{noc}(E_6)$ . The multiplication of  $P_{noc}(E_1)$  and  $P_{noc}(E_2)$  gives  $P_{noc}$  at the root. Similarly,  $P_{noc}$  values at each internal entry in  $R_2$  can be calculated.

The information that  $a_{10}$  dominates both  $a_5$  and  $a_6$  has not been pushed down to leaf-level and is only captured at the entry  $E_4$ ; consequently the captured skyline probabilities for  $a_6$  and  $a_5$  are  $P(a_6) \times (1 - P(a_8))$  (0.64) and  $P(a_5)$  (0.8). Therefore, at  $E_4$ ,  $P_{sky,max} = 0.8$  and  $P_{sky,min} = 0.64$ ;  $P_{new,max} = 1$  and  $P_{new,min} = (1 - P(a_8))$  (0.8). These multiplied by  $P_{new}^{global}$  give the exact values of  $P_{sky,max}$ ,  $P_{sky,min}$ ,  $P_{new,max}$ , and  $P_{new,min}$  at  $E_4$ , respectively. At other entries,  $P_{sky,max}$ ,  $P_{sky,min}$ ,  $P_{new,max}$  and  $P_{new,min}$  take exact values.

Once  $a_2$  removes, at  $E_8$ ,  $P_{old}^{global}$  is updated from 1 to  $(1 - P(a_2)) = 0.9$ .  $\square$

**Removing an Entry.** When an entry  $E$  removes from  $R_1$  or  $R_2$ , we first push down the aggregate information along the path from the root to  $E$  and update the siblings' aggregate information for each entry on the path. For example, when remove  $E_3$ , we first recalculate the max and min probabilities at the root by CalProb ( $R.root$ ), Algorithm 2. Then we push-down  $P_{new}$  and  $P_{old}$  to  $E_1$  and  $E_2$ , respectively by UpdateOldNew ( $R_1.root, E_1$ ) and UpdateOldNew ( $R_1.root, E_2$ ) (Algorithm 3). Then we reset  $P_{old}^{global}$  and  $P_{new}^{global}$  at  $R.root$  by 1. We perform the same operations from  $E_1$  to  $E_3$  and  $E_4$ .

---

**Algorithm 2:** CalProb ( $E$ )

---

```

1 if  $P_{old}^{global}(E) < 1$  then
2   | update  $P_{sky,min}(E)$ ,  $P_{sky,max}(E)$  by multiplying
   |  $\frac{1}{P_{old}^{global}}$ ;
3 end if
4 if  $P_{new}^{global}(E) < 1$  then
5   | update  $P_{sky,min}(E)$ ,  $P_{sky,max}(E)$ ,  $P_{new,min}(E)$ ,
   |  $P_{new,max}(E)$  by multiplying  $P_{new}^{global}$ ;
6 end if

```

---

After  $E$  removes from  $R$ , we recalculate min and max probabilities, as well as  $P_{noc}$  along the path in a bottom-up fashion from  $E$ .

**Inserting an Entry.** In our algorithm, we may need to remove an entry from  $R_1$  and insert it to  $R_2$ , and vice versa. When

---

**Algorithm 3:** UpdateOldNew ( $E, E'$ )

---

```
1 if  $P_{old}^{global}(E) < 1$  then
2   |  $P_{old}^{global}(E') := P_{old}^{global}(E') \times P_{old}^{global}(E)$ ;
3 end if
4 if  $P_{new}^{global}(E) < 1$  then
5   |  $P_{new}^{global}(E') := P_{new}^{global}(E') \times P_{new}^{global}(E)$ ;
6 end if
```

---

an entry  $E$  inserts into  $R_1$  (or  $R_2$ ), we find an appropriate level to insert  $E$ ; that is, the level with the length to the leaf to be the same as the depth of  $E$ . We also first push down the aggregate information, in the same way as a deletion, to the level. After inserting  $E$ , we also recalculate the same aggregate information in the same way as that in a deletion.

**Re-balancing.** When a re-balancing of  $R_1$  or  $R_2$  as an  $R$ -tree is called, we treat it as a deletion followed by an insertion.

### B. Inserting a New Element

As depicted in the last subsection, once a new element  $a_{new}$  arrives, we need to conduct the following tasks: 1) update  $P_{new}$  values of the elements dominated by  $a_{new}$  by multiplying  $(1 - P(a_{new}))$ , 2) remove the elements  $a$  with updated  $P_{new}(a) < q$  from  $R_1$  and  $R_2$ , 3) update  $P_{sky}$  (via  $P_{old}$  and  $P_{new}$ ) values for the elements dominated by some of those removed elements, 4) move elements  $a$  in  $R_1$  with  $P_{sky}(a) < q$  to  $R_2$ , and 5) calculate  $P_{sky}(a_{new})$  and insert it to  $R_1$  or  $R_2$  accordingly since  $P_{new}(a_{new}) = 1$ .

According to Lemma 2, if a remaining element  $a$  in  $S_{N,q}$  is dominated by a removed element  $a'$ , then  $a'$  must be older than  $a$ ; consequently in the task 3) above, we only need to update  $P_{old}$  values. Moreover, by dominance transitivity all the tasks 1) - 4) only need to be conducted against the elements dominated by  $a_{new}$ . Clearly, the task 5) is conducted against entries/elements which dominate  $a_{new}$ . Therefore, it is critical to identify entries/elements in  $R_1$  and  $R_2$  which are fully dominated by  $a_{new}$ , as well as the entries/elements which dominate  $a_{new}$ . Algorithm 4 is an outline of our techniques.

In Algorithm 4, we use  $C1$  to store the entries partially dominate  $a_{new}$ ,  $C2$  to store the entries partially dominated by  $a_{new}$ , and  $C12$  to store the entries which are partially dominated by  $a_{new}$  and partially dominate  $a_{new}$ . Then, we use Probe ( $C1, P_{sky}(a_{new})$ ) and Probe ( $C12, R, P_{sky}(a_{new})$ ) to traverse the two aggregate  $R$ -trees to get all entries/elements dominating  $a_{new}$ . We also use Probe ( $C2, R$ ) and Probe ( $C12, R, P_{sky}(a_{new})$ ) to traverse the two aggregate  $R$ -trees to get all entries/elements fully dominated by  $a_{new}$  and put in  $R$ . Finally, UpdateProb ( $R$ ) conducts tasks 2)-4) and the task 5) is conducted in line 16 by the inserting operation to an aggregate  $R$ -tree ( $R_1$  or  $R_2$ ) as described in Section IV-A. Next, we provide details for the procedures Prob () and UpdateProb().

**Probe ( $C1, P_{sky}(a_{new})$ ) (Algorithm 5).** According to Theorem 1, entries in  $C1$  cannot contain any element which is dominated by  $a_{new}$ . Probe ( $C1, P_{sky}(a_{new})$ ) is to iteratively traverse the aggregate  $R$ -trees to get entries which dominate

---

**Algorithm 4:** Inserting ( $a_{new}$ )

---

```
Input :  $N$ : window size;  $q$ : skyline probability threshold.  $a_{new}$ :
data element.  $R_1$  and  $R_2$ : two aggregate trees on  $SKY_{N,q}$ 
and  $(S_{N,q} - SKY_{N,q})$  respectively.
Output : Updated  $R_1$  and  $R_2$ 
1  $P_{sky}(a_{new}) := P(a_{new})$ ;  $P_{old}(a_{new}) := 1$ ;  $P_{new}(a_{new}) := 1$ ;
2 for each  $E \in \{R_1.root, R_2.root\}$  do
3   | if  $E \prec a_{new}$  then
4     |  $P_{sky}(a_{new}) := P_{sky}(a_{new}) \times P_{noc}(E)$ ;
5     |  $P_{old}(a_{new}) := P_{old}(a_{new}) \times P_{noc}(E)$ ;
6   | else
7     | if  $a_{new} \prec E$  then add  $E$  to  $R$ ;
8     | if  $E \prec_{partial} a_{new}$  &  $a_{new} \prec_{not} E$  then add  $E$  to  $C1$ ;
9     | if  $E \prec_{partial} a_{new}$  &  $a_{new} \prec_{partial} E$  then
10    |   | add  $E$  to  $C12$ ;
11    |   | if  $a_{new} \prec_{partial} E$  &  $E \prec_{not} a_{new}$  then add  $E$  to  $C2$ ;
12 if  $C1 \neq \emptyset$  then Probe ( $C1, P_{sky}(a_{new})$ );
13 if  $C2 \neq \emptyset$  then Probe ( $C2, R$ );
14 if  $C12 \neq \emptyset$  then Probe ( $C12, R, P_{sky}(a_{new})$ );
15 if  $R \neq \emptyset$  then UpdateProb ( $R$ );
16 if  $P_{sky}(a_{new}) \geq q$  then Add  $a_{new}$  to  $R_1$  else add  $a_{new}$  to  $R_2$ 
```

---

$a_{new}$  and then update  $P_{sky}$  and  $P_{old}$  of  $a_{new}$ . In Algorithm 5, we use Dequeue () combining with UpdateOldNew () (Algorithm 3) to push down the aggregate information. Algorithm 6 gives details of Dequeue ().

---

**Algorithm 5:** Probe ( $C1, P_{sky}$ )

---

```
1 while  $C1 \neq \emptyset$  do
2   |  $E :=$  Dequeue ( $C1$ );
3   | for each Children  $E'$  of  $E$  do
4     | UpdateOldNew ( $E, E'$ );
5     | if  $E' \prec a_{new}$  then
6       |  $P_{sky}(a_{new}) := P_{sky}(a_{new}) \times P_{noc}(E')$ ;
7       |  $P_{old}(a_{new}) := P_{old}(a_{new}) \times P_{noc}(E')$ ;
8     | else
9       |   | if  $E' \prec_{partial} a_{new}$  then add  $E'$  to  $C1$ ;
10    |   | if  $E'$  is the last child of  $E$  then
11    |   |   | reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
12 return  $P_{sky}(a_{new})$ ;
```

---

---

**Algorithm 6:** Dequeue ( $C1$ )

---

```
1 if  $C1 \neq \emptyset$  then
2   | get an  $E$  in  $C1$ ; /* remove  $E$  from  $C1$  */;
3   | CalProb ( $E$ ); /* Algorithm 2 */;
4 return  $E$ ;
```

---

**Probe ( $C2, R$ ).** Note that entries in  $C2$  do not contain any elements that dominate  $a_{new}$  according to Theorem 1. Similarly, Probe ( $C2, R$ ) is to iteratively traverse to get all entries/elements which are dominated by  $a_{new}$  and then place them in  $R$ . As a by-product, we push down the aggregate information and update  $P_{new}^{global}$  values of those entries/elements in  $R$ . The details are presented in Algorithm 7.

**Probe ( $C12, R, P_{sky}(a_{new})$ ).** Entries in  $C12$  partially dominate  $a_{new}$  and are also partially dominated by  $a_{new}$ . Consequently, elements contained by entries in  $C12$  might dominate  $a_{new}$  or are dominated by  $a_{new}$ . Probe ( $C12, R, P_{sky}(a_{new})$ ), combing with Algorithms 5 and 7, is to iteratively traverse the aggregate  $R$ -trees to possibly further update  $P_{sky}(a_{new})$  and

**Algorithm 7: Probe ( $C2, R$ )**


---

```

1 while  $C2 \neq \emptyset$  do
2    $E :=$  Dequeue ( $C2$ );
3   for each Children  $E'$  of  $E$  do
4     UpdateOldNew ( $E'$ );
5     if  $a_{new} \prec E'$  then
6        $P_{new}^{global}(E') := (1 - P(a_{new})) \times P_{new}^{global}(E')$ ;
7       add  $E'$  to  $R$ ;
8     else
9       if  $a_{new} \prec_{partial} E'$  then add  $E'$  to  $C2$ ;
10    if  $E'$  is the last child of  $E$  then
11      reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
12 return  $R$ ;

```

---

add more to  $R$ . We present the details below in Algorithm 8.

**Algorithm 8: Probe ( $C12, R, P_{sky}(a_{new})$ )**


---

```

1 while  $C12 \neq \emptyset$  do
2    $E :=$  Dequeue ( $C12$ );
3   for each Children  $E'$  of  $E$  do
4     UpdateOldNew ( $E'$ );
5     if  $a_{new} \prec E'$  then
6        $P_{new}^{global}(E') := (1 - P(a_{new})) \times P_{new}^{global}(E')$ ;
7       add  $E'$  to  $R$ ;
8     else
9       if  $a_{new} \prec_{partial} E' \ \& \ E' \prec_{not} a_{new}$  then
10        add  $E'$  to  $C2$ ;
11       if  $a_{new} \prec_{not} E' \ \& \ E' \prec_{partial} a_{new}$  then
12        add  $E'$  to  $C1$ ;
13       if  $a_{new} \prec_{partial} E' \ \& \ E' \prec_{partial} a_{new}$  then
14        add  $E'$  to  $C12$ ;
15       if  $E' \prec a_{new}$  then
16          $P_{sky}(a_{new}) := P_{sky}(a_{new}) \times P_{noc}(E')$ ;
17          $P_{old}(a_{new}) := P_{old}(a_{new}) \times P_{noc}(E')$ ;
18       if  $E'$  is the last child of  $E$  then
19         reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
20 if  $C1 \neq \emptyset$  then Probe ( $C1, P_{sky}$ ) (Algorithm 5);
21 else return  $P_{sky}(a_{new})$ ;
22 if  $C2 \neq \emptyset$  then Probe ( $C2, R$ ) (Algorithm 7);
23 else return  $R$ ;

```

---

**UpdateProb ( $R$ ).**  $R$  contains all entries/elements which are fully dominated by  $a_{new}$  and obtained by Probe ( $C12, R, P_{sky}(a_{new})$ ) and Probe ( $C2, R$ ). Note that in our implementation, we use a link list to point to all these entries/elements in  $R$ . UpdateProb ( $R$ ) is to traverse those entries in  $R$ , along the aggregate  $R$ -trees to which they belong, to detect and remove entries/elements with the updated  $P_{new}$  values smaller than  $q$ . Moreover, it also updates the  $P_{old}$  values of remaining elements in  $R$  which are dominated by some removed elements, as well as detects the remaining elements in  $R$  with  $P_{sky} < q$ . Algorithm 9 provides details.

*Lines 1-11:* Iteratively detect the elements/entries to be removed (i.e. with  $P_{new} < \theta$ ) and put them to  $R_3$ .

*Lines 12:* UpdateOld ( $R_3, R_4$ ) is to update the values of  $P_{old}^{global}$  of elements/entries in  $R_4$  dominated by some in  $R_3$  as follows. For each pair  $E1 \in R_3$  and  $E2 \in R_4$ ,

if  $E1$  fully dominates  $E2$ , then update  $P_{old}^{global}(E2)$  by multiplying  $P_{noc}(E1)$ ; otherwise, if  $E1$  partially

**Algorithm 9: UpdateProb ( $R$ )**


---

```

1 while  $R \neq \emptyset$  do
2    $E :=$  Dequeue ( $R$ );
3   if  $P_{new, min}(E) < q \leq P_{new, max}(E)$  then
4     for each Children  $E'$  of  $E$  do
5       UpdateOldNew ( $E', E$ );
6       add  $E'$  to  $R$ ;
7       if  $E'$  is the last child of  $E$  then
8         reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
9   else
10    if  $P_{new, min}(E) \geq q$  then add  $E$  to  $R_4$ ;
11    else add  $E$  to  $R_3$ ; /*  $P_{new, max}(E) < q$  */;
12 if  $R_3 \neq \emptyset$  and  $R_4 \neq \emptyset$  then UpdateOld ( $R_3, R_4$ );
13 if  $R_3 \neq \emptyset$  then Remove ( $R_3$ );
14 if  $R_4 \neq \emptyset$  then Place ( $R_4$ );

```

---

dominates  $E2$  then put the children of  $E1$  to  $R_3$  and the children of  $E2$  to  $R_4$  for the next iteration.

In our implementation, we mark entries from  $R$  (i.e.,  $R_3$  and  $R_4$ ) within  $R_1$  and  $R_2$ . Then, we use the *synchronous traversal* paradigm [11] to traverse  $R_3$  and  $R_4$  by following the  $R$ -tree structures of the entries in  $R_3$  and  $R_4$ . Here, we create a dummy root for  $R_3$  with all entries in  $R_3$  to be children of the root; similar treatments are done for  $R_4$ .

*lines 13:* We remove entries/elements in  $R_3$  from  $R_1$  and  $R_2$  as what discussed in Section IV-A.

*lines 14:* Place ( $R_4$ ) is to determine elements/entries in  $R_4$  to be in  $R_1$  or  $R_2$ . In fact, we only need to check  $R_4 \cap R_1$  according to Corollaries 1 and 2; it is conducted as follows. For each entry  $E \in R_4 \cap R_1$ , we use depth-first search to find out all its highest level decedent entries with  $P_{sky, min}$  greater than  $q$  - Algorithm 10. In lines 10-11 of Algorithm 10, we first remove  $E$  from  $R_1$  in the way as described in Section IV-A. Then, we insert  $E$  into  $R_2$  in the way as described in Section IV-A.

**Algorithm 10: Place ( $R_4$ )**


---

```

1 while  $R_1 \cap R_4 \neq \emptyset$  do
2    $E :=$  Dequeue ( $R_1 \cap R_4$ );
3   if  $P_{sky, min}(E) < q \leq P_{sky, max}(E)$  then
4     for each Children  $E'$  of  $E$  do
5       UpdateOldNew ( $E'$ );
6       add  $E'$  to  $R_1 \cap R_4$ ;
7       if  $E'$  is the last child of  $E$  then
8         reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
9   else
10    if  $P_{sky, max}(E) < q$  then
11      Move  $E$  from  $R_1$  to  $R_2$ ;

```

---

**C. Expiration**

Once an element  $a_{old}$  expires, we first check if it is in  $S_{N, q}$ . If it is in  $S_{N, q}$  then we need to increase the  $P_{old}$  values for elements dominated by  $a_{old}$ . After that, we need to determine the elements that need to be moved from  $R_2$  to  $R_1$ . Algorithm 11 below presents details.

In Algorithm 11, Move ( $R \cap R_2$ ) is to move the elements in  $R \cap R_2$  with updated skyline probability not smaller than  $q$  to  $R_1$ . It is executed in the same way as Place ( $R_4$ ) but replace

---

**Algorithm 11: Expiring ( $a_{old}$ )**

---

```
1 if  $a_{old} \in S_{N,q}$  then
2   Remove ( $a_{old}$ );
3   for  $E \in \{R_1.root, R_2.root\}$  do
4     if  $a_{old} \prec E$  then
5        $P_{old}(E) = P_{old}(E)/(1 - P(a_{old}))$ ;
6       add  $E$  to  $R$ ;
7     else
8       if  $a_{old} \prec_{partial} E$  then add  $E$  to  $C$ ;
9   while  $C \neq \emptyset$  do
10     $E :=$  Dequeue ( $C$ );
11    for each Children  $E'$  of  $E$  do
12      UpdateOldNew ( $E'$ );
13      if  $a_{old} \prec E'$  then
14         $P_{old}(E') := P_{old}(E')/(1 - P(a_{old}))$ ;
15        add  $E'$  to  $R$ ;
16      else
17        if  $a_{old} \prec_{partial} E'$  then add  $E'$  to  $C$ ;
18      if  $E'$  is the last child of  $E$  then
19        reset  $P_{new}^{global}(E)$  and  $P_{old}^{global}(E)$  to 1;
20 if  $R \neq \emptyset$  then Move ( $R \cap R_2$ );
```

---

$R_1 \cap R_4$  by  $R \cap R_2$  and move from  $R_2$  to  $R_1$  instead of  $R_1$  to  $R_2$ .

#### D. Multiple Confidences

**Continuous queries** Different users may specify different confidences. Suppose that users specify  $k$  confidences  $q_1, q_2, \dots, q_k$  where  $q_i < q_{i-1}$ . Our techniques for a single given confidence can be immediately extended to cover multiple confidences as follows.

Instead of maintaining a single solution set  $R_1$  in Algorithm 11, we maintain  $k$  solution sets  $R_1, R_2, \dots, R_k$  such that elements in  $R_i$  (for  $2 \leq i \leq k$ ) have the skyline probabilities in  $[q_i, q_{i-1})$  where  $q_0 = 1$  and  $R_{k+1}$  keeps the elements in  $(S_{N,q_k} - \cup_{i=1}^k R_i)$ . Those  $R_i$  for  $i = 1$  to  $(k + 1)$  are also maintained as aggregate  $R$ -trees with the same aggregate information.

All the techniques from Algorithm 11 are immediately applicable except that now in Algorithm 9, we need to detect where to place some elements in  $R \cap R_i$  for  $i \leq k$ ; that is, we need to consider all  $R_j$  for  $i < j < k + 1$ . In Algorithm 11, now we need to detect where to move some elements in  $R_{k+1}$ ; that is, we need to consider  $R_j$  (for  $1 \leq j \leq k$ ) instead of just  $R_1$  in the case of single confidence.

**Ad-hoc Queries.** Users may also issue an ad-hoc query, “find the skyline with skyline probability at least  $q'$ ”. Assume that currently we maintain  $k$  skylines as discussed above and  $q' \geq q_k$ . Then, we first find an  $R_i$  such that  $q_i \leq q' < q_{i-1}$ ; clearly elements  $\{R_j: j < i - 1\}$  are contained in the solution. We can apply the search paradigm in Place ( $R_4$ ) (Algorithm 10) to get all elements in  $R_i$  with skyline probabilities  $\geq q$  but without updating aggregate probabilities information.

#### E. Algorithm Analysis

**Correctness.** Our sliding window techniques maintain aggregate information against  $S_{N,q}$  and then get skyline according to the skyline probabilities restricted to  $S_{N,q}$ , Theorems,

Lemmas and Corollaries in Section III-A ensure that our algorithms are correct.

**Space Complexity.** Clearly, in our algorithm we use aggregate- $R$  trees to keep each element in  $S_{N,q}$  and each element is kept only once. Thus, the space complexity is  $O(|S_{N,q}|)$ .

**Time Complexity.** It seems hard to provide a sensible time complexity analysis; nevertheless, our experiment demonstrates the algorithms in this section is much faster than the trivial algorithm against  $S_{N,q}$  as what discussed in the beginning of this section.

## V. PERFORMANCE EVALUATION

In this section, we only evaluate our techniques since this is the first paper studying the problem of probabilistic skyline computation over sliding windows. Specifically, we implement and evaluate the following techniques.

**SSKY Techniques** presented in Section IV to continuously compute  $q$ -skyline (i.e., skyline with the probability not less than a given  $q$ ) against a sliding window.

**MSKY Techniques** in Section IV-D to continuously computing multiple  $q$ -skylines currently regarding multiple given probability thresholds.

**QSKY Techniques** in Section IV-D to processing an ad-hoc skyline query with a probability threshold.

All algorithms are implemented in C++ and compiled by GNU GCC. Experiments are conducted on PCs with Intel Xeon 2.4GHz dual CPU and 4G memory under Debian Linux. Our experiments are conducted on both real and synthetic datasets.

**Real dataset** is extracted from the stock statistics from NYSE (New York Stock Exchange). We choose 2 million stock transaction records of Dell Inc. from *Dec 1st 2000* to *May 22nd 2001*. For each transaction, the average price per volume and total volume are recorded. This 2-dimensional dataset is referred to as *stock* in the following. We randomly assign a probability value to each transaction; that is, probability values follows *uniform* distribution. Elements' arrival order is based on their transaction time.

**Synthetic datasets** are generated as follows. We first use the methodologies in [3] to generate 2 million data elements with the dimensionality from 2 to 5 and the spatial location of data elements follow two kinds of distributions, *independent* and *anti-correlated*. Then, we use two models *uniform* or *normal* distributions to randomly assign occurrence probability of each element to make them be uncertain. In *uniform* distribution, the occurrences probability of each element takes a random value between 0 and 1, while in the *normal* distribution, the mean value  $P_\mu$  varies from 0.1 to 0.9 and standard deviation  $S_d$  is set 0.3. We assign a random order for elements' arrival in a data stream.

**Choosing  $q$ .**  $q$  is the probability threshold in evaluating efficiency of query processing. To evaluate SSKY, we use 0.3 as a default value of  $q$ , while to evaluate MSKY with  $k$  given probability thresholds  $q_1, \dots, q_k$ , we let these  $k$

values evenly spread  $[0.3, 1]$ . To evaluate QSKY, we issue 1000 queries across  $[q, 1]$  where  $q$  is the minimum probability threshold when multiple thresholds are pre-given for multiple continuous skylines. We record average time to process these 1000 queries.

Table II summarizes parameters and corresponding default values. **In our experiments, all parameters take default values unless otherwise specified.**

TABLE II  
SYSTEM PARAMETERS

Notation	Definition (Default Values)
$n$	Number of points in the dataset (2M)
$N$	Sliding Window size (1M)
$d$	Dimensionality of the of the dataset (3)
$D$	Dataset (Anti)
$D_P$	Probabilistic distribution of appearance ( <i>uniform</i> )
$P_\mu$	expected appearance probability (0.5)
$q$	probabilistic threshold (0.3)
$q'$	probabilistic threshold $q' (q \leq q' \leq 1)$

In our experiments, we evaluate the efficiency of our algorithm as well as space usage against dimensionality, size of sliding window, probabilistic threshold, distribution of objects' spatial location and appearance probability distribution.

#### A. Evaluate Space Efficiency

We evaluate the space usage in terms of the number of uncertain elements kept in  $S_{N,q}$  against different settings. As this number may change as the window slides, we record the maximal value over the whole stream. Meanwhile, we also keep the maximal number of  $SKY_{N,q}$ .

The first set of experiments is reported in Figure 4 where 4 datasets are used: Inde-Uniform (Independent distribution for spatial locations and Uniform distribution for occurrence probability values), Anti-Uniform, Anti-Normal, and Stock-Uniform. We record the maximum sizes of  $S_{N,q}$  and  $SKY_{N,q}$ . It is shown that very small portion of the 2-dimensional dataset needs to be kept. Although this proportion increases with the dimensionality rapidly, our algorithm can still achieve a 89% space saving even in the worst case, 5 dimensional *anti-correlated* data. Size of  $SKY_{N,q}$  is much smaller than that of candidates. Since the *anti-correlated* dataset is the most challenging, it will be employed as the default dataset in the following.

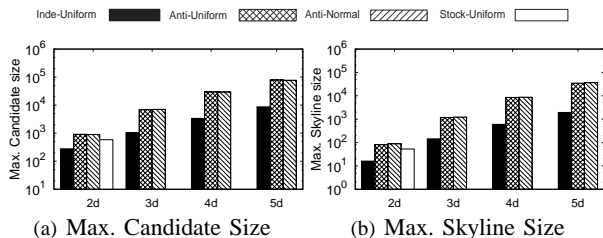


Fig. 4. Space Usage vs Diff. Data set

The second set of experiment evaluates the impact of sliding window size  $N$  on the space efficiency. As depicted in Figure 5, the space usage is sensitive towards the increment of window size.

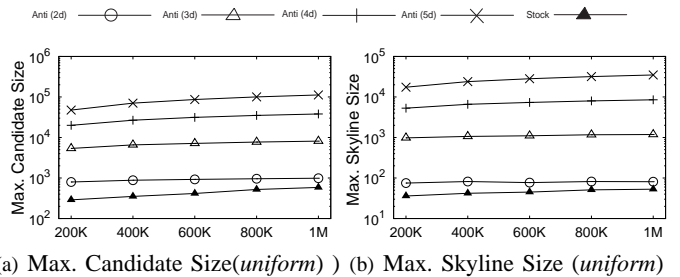


Fig. 5. Space Usage vs Window Size

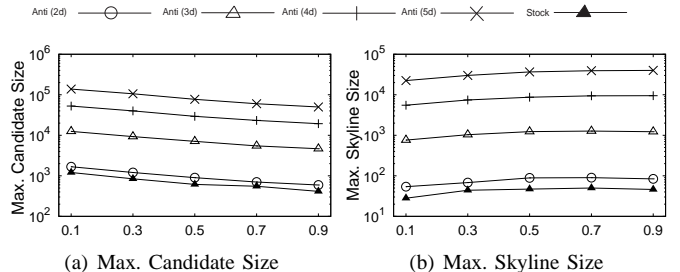


Fig. 6. Space Usage vs Appearance Probability

Figure 6 reports the impact of occurrence probability distribution against the space usage and number of skyline points on different datasets. The occurrence probability follows *normal* distribution and the mean of the appearance probability  $P_\mu$  increases from 0.1 to 0.9. It demonstrates that the smaller the average appearance probability of the points, the more points will be kept in  $S_{N,q}$ . As shown in Figure 6(a), the size of the candidate decreases with the increase of average appearance probability. Interestingly, although the candidate size is large with smaller average occurrence probability, the number of probabilistic skyline is small, as illustrated in Figure 6(b). This is because the small occurrence probability prevents the uncertain objects from becoming probabilistic skyline.

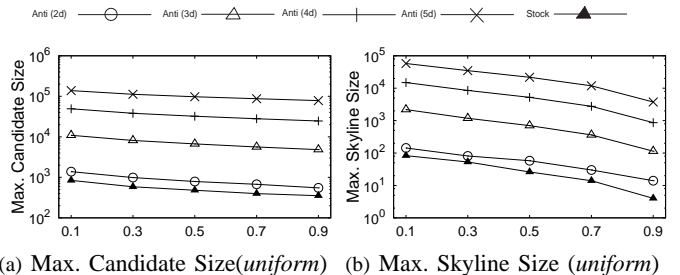


Fig. 7. Space Usage vs Probability threshold

Figure 7 reports the effect of probabilistic threshold  $q$  on space efficiency. As expected, both candidate set size and skyline set size drop as  $q$  increases.

#### B. Evaluation Time Efficiency

We evaluate the time efficiency of our continuous query processing techniques, SSKY and MSKY, as well as ad-hoc query processing technique QSKY. We first compare SSKY with the trivial algorithm against  $SKY_{N,q}$  as described in the beginning of Section IV. We find it is about 20 times slower than SSKY against anti (3d). Thus, we exclude the trivial

algorithm from further evaluation.

Since the processing time of one element is too short to capture precisely, we record the average time for each batch of 1K elements to estimate the delay per element.

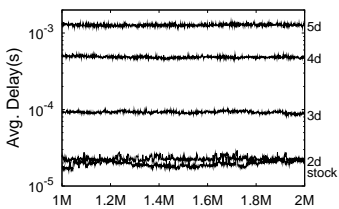


Fig. 8. Time Efficiency vs  $n$

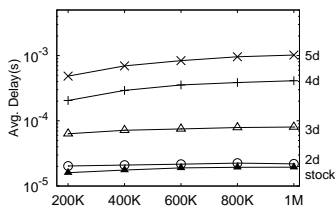


Fig. 9. Avg. Delay vs  $W$

The first set of experiment is depicted in Figure 8. It shows that SSKY is very efficient, especially when the dimensionality is low. For 2 dimensional dataset, SSKY can support a workload where elements arrive at the speed of more than 38K per second even for *stock* and *anti-correlated* dataset. For 5d *anti-correlated* data, our algorithm can still support up to 728 elements per second, which is a medium speed for data streams.

Figure 9 evaluates the system scalability towards the size of the sliding window. The performance of SSKY is not sensitive to the size of sliding window. This is because the candidate size increases slowly with  $N$ , as reported in Figure 5.

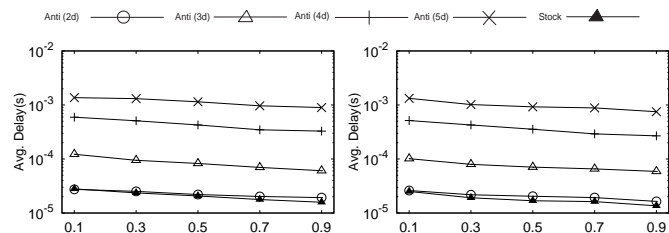


Fig. 10. Avg. Delay vs  $P_\mu$

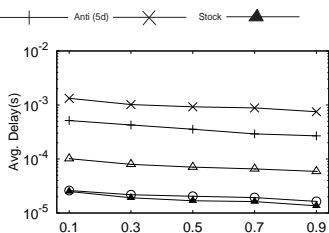


Fig. 11. Avg. Delay vs  $q$

Figure 10 evaluates the impact of occurrence probability distribution on time efficiency of SSKY where normal distribution is used for probability values. As expected, large  $P_\mu$  leads to better performance since the candidate size is small when  $P_\mu$  is large.

Figure 11 evaluates the effect of probability threshold  $q$  on SSKY. Since both size of candidate set and skyline objects set are small when  $q$  is large as depicted in Figure 7, SSKY is more efficient when  $q$  increases.

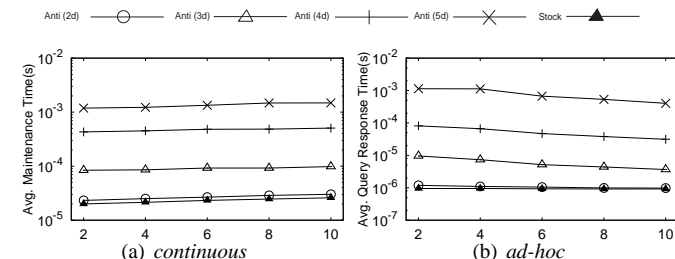


Fig. 12. Query Cost vs  $|Q|$

The last experiment evaluates the efficiency of our multi probability thresholds based continuous query processing tech-

niques MSKY and ad-hoc query processing techniques. Results are reported in Figures 12(a) and 12(b), respectively. As expected, Figure 12(a) shows that cost to process each element by MSKY increases when  $k$  increases, while Figure 12(b) shows the ad-hoc query processing cost decreases when  $k$  increases.

### C. Summary

As a short summary, our performance evaluation indicates that we only need to keep a small portion of stream objects in order to compute the probabilistic skyline over sliding windows. Moreover, our continuous query processing algorithms are very efficient and can support data streams with high speed for 2d and 3d datasets. Even for the most challenging data distribution, *anti-correlated*, we can still support the data stream with medium speed of more than 700 elements per second when dimensionality is 5.

## VI. APPLICATIONS

The techniques developed in this paper can be immediately extended to the following applications.

**Probabilistic Top-k Skyline Elements.** Given an uncertain data stream, a threshold  $q$ , and a sliding window size  $W$ , find the  $k$  skyline points with the highest skyline probabilities (but not smaller than  $q$ ).

We can apply our algorithms in Section IV to remove points with  $P_{new} < q$ , update aggregate information at each entry, probabilities ( $P_{sky}$ ,  $P_{old}$ ,  $P_{new}$ , etc). We do not move any elements in  $R_4 \cap R_1$  to  $R_2$ . Instead, we treat  $R_1$  and  $R_2$  as two “heap trees”. In fact, both  $R_1$  and  $R_2$  maintain two heaps on  $P_{sky}$ : 1) min-heap, and 2) max-heap; this is because we keep  $P_{sky,min}$  and  $P_{sky,max}$  at each entry. We use min-heap on  $R_1$  and max-heap on  $R_2$  to move elements in top- $k$  from  $R_2$  to  $R_1$  and move elements in  $R_1$  but not in top- $k$  to  $R_2$ .

**Time Stamp based Sliding Windows.** In such a model, we expire an old element if it is not within a pre-given most recent time period  $T$ . Our techniques can be immediately extended to sliding windows based on the most recent time period  $T$ .

**Object with Multiple Elements.** Suppose that an uncertain stream contains a sequence of objects such that each object consists of a set of instances [22] or PDF. In fact, our skyline probability model is a special case of the model in [22]. In our sliding window model, we assume that each object is *atomic*.<sup>1</sup> Then we want to compute objects with skyline probabilities not smaller than  $q$ . It can be immediately verified that all our techniques are immediately applicable to discrete cases except we compute skyline probability in a different way; that is, based on the definition in [22]. For continuous cases, we can use Monte-Carlo sampling method [16] to discrete them.

## VII. RELATED WORK

We review related work in two aspects, skylines and uncertain data streams. To the best of our knowledge, this paper

<sup>1</sup>When an object arrives, all its instances arrive; when an object expires, all its instances expire.

is the first one to address the problem of skyline queries on uncertain data streams.

**Skylines.** Börzsönyi *et al* [3] first study the skyline operator in the context of databases and propose an SQL syntax for the skyline query. They also develop two computation techniques based on *block-nested-loop* and *divide-and-conquer* paradigms, respectively. Another *block-nested-loop* based technique SFS (*sort-filter-skyline*) is proposed by Chomicki *et al* [7], which takes advantage of a pre-sorting step. SFS is then significantly improved by Godfrey *et al* [10]. The *progressive* paradigm that aims to output skyline points without scanning the whole dataset is firstly proposed by Tan *et al* [24]. It is supported by two auxiliary data structures, *bitmap* and *search tree*. Kossmann *et al* [18] present another progressive technique based on the nearest neighbor search technique. Papadias *et al* [21] develop a *branch-and-bound* algorithm (BBS) to progressively output skyline points based on R-trees with the guarantee of minimal I/O cost. Variations of the skyline operator have also been extensively explored, including skylines in a distributed environment [2], [12], skylines for partially-ordered value domains [4], skyline cubes [23], [26], [27], reverse skylines [9], approximate skylines [5], [6], [17], etc.

Skyline queries processing in data streams is investigated by Lin *et al* [20] against various sliding windows. Tao *et al* [25] independently develop efficient techniques to compute sliding window skylines.

The skyline query processing on uncertain data is firstly approached by Pei *et al* [22] where *Bounding-pruning-refining* techniques are developed for efficient computation. Lian *et al* [19] combine reverse skylines [9] with uncertain semantics and model the *probabilistic reverse skyline* query in both monochromatic and bichromatic fashion. Efficient pruning techniques are developed to reduce the search space for query processing.

**Uncertain Data Streams.** Although numerous research aspects have been addressed on managing certain stream data, works on uncertain data streams have abounded only very recently. Aggregates over uncertain data streams have been studied recently [8], [13], [14]. Problems such as clustering uncertain data stream [1], frequent items retrieval in probabilistic data streams [28], and sliding window top-k queries on uncertain streams [15] are also investigated. Since skyline queries are inherently different from these problems, techniques proposed in none of the above papers can be applied directly to the problems studied in this paper.

## VIII. CONCLUSION

In this paper, we investigate the problem of efficiently computing skyline against sliding windows over an uncertain data stream. We first model the probability threshold based skyline problem. Then, we present a framework which is based on efficiently maintaining a candidate set. We show that such a candidate set is the minimum information we need to keep. Efficient techniques have been presented to process continuous queries. We extend our techniques to concurrently

support processing a set of continuous queries with different thresholds, as well as to process an ad-hoc skyline query. Finally, we show that our techniques can also be extended to support probabilistic top-*k* skyline against sliding windows over an uncertain data streams. Our extensive experiments demonstrate that our techniques can deal with a high-speed data stream in real time.

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