Quality-Driven Disorder Handling for M-way Sliding Window Stream Joins

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Abstract—Sliding window join is one of the most important operators for stream applications. To produce high quality join results, a stream processing system must deal with the ubiquitous disorder within input streams which is caused by network delay, asynchronous source clocks, etc. Disorder handling involves an inevitable tradeoff between the latency and the quality of produced join results. To meet different requirements of stream applications, it is desirable to provide a user-configurable result-quality latency vs. result-quality tradeoff. Existing disorder handling approaches either do not provide such configurability, or support only user-specified latency constraints.

In this work, we advocate the idea of quality-driven disorder handling, and propose a buffer-based disorder handling approach for sliding window joins, which minimizes sizes of input-sorting buffers, thus the result latency, while respecting user-specified result-quality requirements. The core of our approach is an analytical model which directly captures the relationship between sizes of input buffers and the produced result quality. Our approach is generic. It supports m-way sliding window joins with arbitrary join conditions. Experiments on real-world and synthetic datasets show that, compared to the state of the art, our approach can reduce the result latency incurred by disorder handling by up to 95% while providing the same level of result quality.

I. INTRODUCTION

In the past two decades, we have witnessed an increasing interest in real-time processing of data streams generated by online sources such as sensor networks [1] and financial markets [2]. A stream tuple is often tagged with a timestamp as it is generated at a data source, e.g., a sensor. For many stream applications, m-way sliding window joins (MSWJ) are key operators for discovering correlations among different streams, e.g., finding similar news items from different news sources [3]. In general, an MSWJ operator works as follows [4]–[6]: for each newly arrived tuple  from any input stream, the operator invalidates expired tuples in windows on all other input streams based on the timestamp of ; probes all remaining tuples in those windows, and produces derived result tuples that satisfy the predefined join condition . The timestamp assigned to a result tuple is the maximum timestamp among its deriving input tuples.

One big challenge in data stream processing is to handle stream disorder with respect to tuple timestamps. For multi-input operators such as MSWJ, stream disorder enters in two forms: First, each individual stream could be out of order; namely, tuples within the stream do not arrive in non-decreasing timestamp order ( intra-stream disorder). Second, even if each individual stream is timestamp-ordered, tuples from different streams could arrive out of order (inter-stream disorder). Disorder is ubiquitous in real-world data streams, and handling it is essential to avoid missed and out-of-order join results, we need to either sort input tuples to process them in a timestamp order [9], [10], or sort result tuples [10], [11]. In either case, the latency of the results is increased. This implies that high result quality and low result latency are two conflicting targets in disorder handling. Many applications, such as network traffic monitoring and environment monitoring, allow doing incomplete sorting and hence losing a small fraction of joins.

1 Note that some join algorithms (e.g., [7], [8]) would miss the result tuple (); because upon receiving a new tuple, they invalidate expired tuples in windows on all streams. Hence, at the arrival of , the tuple would expire from the window on .
results to obtain low result latency. However, it is still desired that the result quality is controlled at an acceptable level.

Based on observations that (1) disorder handling involves an inevitable tradeoff between the result latency and the result quality, and (2) different applications may have different tradeoff requirements, we believe that a disorder handling approach should support user/application-configurable result-latency vs. result-quality tradeoff. Existing disorder handling approaches either do not provide this configurability (e.g., [12], [13]), or support disorder handling only under user-specified latency constraints (e.g., [14], [15]). As a complement to the state of the art, in our previous work [16], [17], we proposed the idea of quality-driven disorder handling, with the objective of minimizing the result latency while honoring user-specified result-quality requirements. In [16], [17], we introduced an adaptive, quality-driven, buffer-based disorder handling approach for processing sliding window aggregate queries. The size of the buffer for sorting input tuples was dynamically adjusted using a proportional-derivative (PD) controller.

In this paper, we extend our focus beyond unary stream processing operators to n-ary operators, in particular, the MSWJ operator. In contrast to the existing work such as [15] and [18], we assume the most common scenario, where no facilitating information such as punctuations is available in input streams to indicate the stream progress; hence, we again employ the buffer-based disorder handling approach. However, due to the difference in the operator semantics, our result-quality metric for joins is different from that for aggregates. From the discussion above, we can see that the output of an MSWJ under incomplete disorder handling is only a subset of the output produced when the input streams are in order and synchronized with each other. Hence, we adopt the metric recall, which is often used in work about load shedding for joins [3], [8], [19]. In addition, the PD controller, which was used in our previous work for adapting the size of the input buffer, treats the relationship between the applied buffer size and the consequent result quality as a black box; as a result, in one adaptation step, it is not able to directly determine the optimal buffer size for meeting the result-quality requirement. In this paper, we propose a new adaptation method, which allows searching for the optimal buffer size directly at one adaptation step, by analytically modeling the relationship between the applied buffer size and the produced result quality. Moreover, the contribution of an input tuple to the quality of join results is determined by its productivity, i.e., the number of join results that it can derive. Clearly, the unsuccessful handling of a delayed tuple with a high productivity has a higher impact on the result quality than the unsuccessful handling of a delayed tuple with a low productivity. Hence, the proposed analytical model also considers the correlation between the delay and the productivity of tuples.

In summary, our work makes the following contributions:

- We extend the application of the idea of quality-driven disorder handling to MSWJ queries executed over out-of-order and unsynchronized data streams. The objective is to minimize the result latency incurred by disorder handling while respecting the user-specified result-quality requirement. To this end, we propose a generic buffer-based disorder handling approach which supports MSWJs with arbitrary join conditions. (Sec. III)
- We show that it suffices to use a buffer of the same size on each input stream to deal with its intra-stream disorder, which may sound non-intuitive since different streams normally have different disorder characteristics. (Sec. III-B)
- We analytically model the relationship between the applied buffer sizes and the consequent quality (i.e., recall) of produced join results. Based on this model, we propose a new buffer-size adaptation method, which can search for the optimal buffer size to meet the user-specified result-quality requirement at each adaptation step. (Sec. IV-A)
- We incorporate the consideration of potential correlation between the delay and the productivity of tuples into the proposed analytical model. Inspired by the work of [3], [20], we learn this correlation at query runtime by profiling the output of the join. This method is light-weight and can work with arbitrary join conditions. (Sec. IV-B)

We introduce related concepts and notations in Sec. II. We discuss how the proposed approach can be applied in the context of distributed MSWJ processing in Sec. V. We conduct experiments on both real-world and synthetic datasets to study the effectiveness of our solution. The results are reported in Sec. VI. We review related work in Sec. VII and conclude the paper in Sec. VIII.

II. PRELIMINARIES

A. MSWJ over Data Streams

An MSWJ has \( m \geq 2 \) input streams \( S_1, S_2, \ldots, S_m \), and an optional join condition \( p^8 \) which may contain one or more join predicates. We denote the \( j \)-th arrived tuple in stream \( S_i \) by \( e_{i,j}, \) and its timestamp by \( e_{i,j}^t. \) We define the local current time \( T \) of stream \( S_i \) as the maximum timestamp among already arrived tuples in \( S_i \), i.e., \( T = \max\{e_{i,j}^t | e_{i,j} \in S_i\} \). A stream \( S_i \) is considered to be out of order if it contains tuples \( e_{i,j} \) and \( e_{i,k} \) such that \( j < k \) and \( e_{i,j}^t > e_{i,k}^t. \) The tuple \( e_{i,k} \) in this case is called an out-of-order tuple in \( S_i \). For a tuple \( e_i \) in any stream \( S_i \), the delay of the tuple is denoted by \( \text{delay}(e_i) \), and is defined as the difference between the \( i^\text{th} \) updated at the arrival of \( e_i \) and the timestamp of \( e_i \), i.e., \( \text{delay}(e_i) = |T - e_i^t| \). We assume that the delay of any input tuple is bounded, but do not require knowing this upper bound a priori. At the query runtime, we take the maximum observed tuple delay as an estimation of this upper bound. In the following, we omit the subscript of a tuple completely or keep only the part that indicates the input stream, if the omitted part is not important in the context of the discussion.

We denote the time skew between a pair of streams \( S_i \) and \( S_j \) (\( i \neq j \)) by \( \text{skew}(S_i, S_j) \), and define it as the absolute difference between the local current time of \( S_i \) and \( S_j \), i.e., \( \text{skew}(S_i, S_j) = |T - J| \). As \( T \) and \( J \) are updated by newly arrived tuples in \( S_i \) and \( S_j \), respectively, \( \text{skew}(S_i, S_j) \) often varies during the lifetime of \( S_i \) and \( S_j \). Furthermore, given \( m \) streams, we refer to the stream with the smallest \( T \) as the slowest stream in terms of the timestamp progress.

Each input stream \( S_i \) is associated with a sliding window [21], whose size is specified by the user. In this paper, we focus on time-based sliding windows, where the window size \( W_i \) is defined in the number of time units. Each input tuple with a low productivity. Hence, the proposed analytical model also considers the correlation between the delay and the productivity of tuples.

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8Incomplete sorting of result tuples leads to loss of join results as well, because result tuples that are still out of order after sorting are discarded to fulfill the "in-order output" requirement.

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8For brevity, we use the superscript \( i \) before \( T \) to denote a property of input tuples.
TABLE I. LIST OF NOTATIONS

| Notations | Description |
|-----------|-------------|
| $S_i$     | $i$-th input stream |
| $e_{i,j}$ | $j$-th arrived tuple in $S_i$ |
| $T_{i}$   | Local current time of $S_i$; $T = \max_{e_{i,j} \in S_i} e_{i,j}.ts$ |
| $\skew(S_i, S_j)$ | Time skew between $S_i$ and $S_j$; $\skew(S_i, S_j) = |T - T'|$ |
| $\delay(e_{i,j})$ | Delay of tuple $e_{i,j}$, $\delay(e_{i,j}) = T - e_{i,j}.ts$ |
| $\gamma(P)$ | Recall of result tuples of an MSWJ measured based on $P$ |
| $\Gamma$  | User-specified requirement on $\gamma(P)$ |
| $K_i$     | Dynamic size of the buffer in the $K$-slack component for stream $S_i$ |
| $T_{max}$ | Current maximum timestamp among tuples released from $\text{Synchronizer}$ |
| $\kappa$  | Implicit buffer size in the $\text{Synchronizer}$ that contributes to handling the intra-stream disorder of $S_i$ |
| $\rho$    | Data arrival rate of $S_i$ |
| $L$       | Size of a basic window (system param.) |
| $\gamma(K, L)$ | Estimated recall of results produced within $L$ under a give value of $K$ |
| $\Pi^*$  | Requirement on $\gamma(K, L)$; derived from user-specified $\Gamma$ |
| $N_{\text{opt}}(K, L)$ | Join result size within $L$ under given configuration of $K$ |
| $N_{\text{prod}}(K, L)$ | Cross-join result size corresponding to $N_{\text{opt}}(K, L)$ |
| $N_{\text{sync}}(K, L)$ | Cross-join result size corresponding to $N_{\text{prod}}(K, L)$ |
| $D_{\text{p}}, D'_{\text{p}}$ | Random variables representing the coarse-grained tuple delay in $S_i$ and in the corresponding stream of $S_i$ received by join operator, respectively |
| $f_{\text{true}}, f_{\text{prod}}$ | Probability density functions of $D_{\text{p}}, D'_{\text{p}}$, respectively |

stream could have a different window size. Semantically, an input tuple $e_{j}$ from any stream $S_i$ joins with the subset $\{e_{j}[|w_j|] \leq W_j \leq e_{j}.ts \leq e_{j}.ts + W_j\}$ of each stream $S_j$ ($j \neq i$). A result tuple $\langle e_{1}, e_{2}, ..., e_{p}\rangle$ is produced if the join condition $p^{*}$ is passed. The timestamp assigned to the result tuple is $\max_{e_{j}.ts \in [1, m]}$. Finding the optimal join order is orthogonal to our focus, and any existing work in this area (e.g., [5], [20]) can be applied.

To guarantee an ordered output stream, we adopt the strategy of enforcing timestamp-ordered processing of tuples from all input streams [9], [10]; namely, the disorder handling is performed prior to the actual join operation. If the disorder handling is incomplete, then the join output (in terms of both the set of result tuples and the order between the result tuples with respect to their timestamps) would be the same as the join output when input streams are totally in order and synchronized with each other. We define the number of result tuples produced at the arrival of a tuple $e$ in this case as the productivity of $e$. Details about our disorder handling solution are given in Sec. III and Sec. IV.

B. Result-Quality Metric

When the disorder handling is incomplete, only a fraction of true results (i.e., results produced when streams are in order and synchronized) will be produced. The fraction of actually produced results is defined as the recall [8], and is used as the result-quality metric for MSWJs. In our work, each time the recall of results needs to be measured, instead of considering all join results produced so far, we consider the join results whose timestamps are within the last $P$ time units; $P$ is termed the result-quality measurement period, and it is a user-specified requirement. We introduce $P$ for two reasons: (1) it allows a user to specify the quality measurement period that is of his own interest; (2) with a full-history-based recall definition, it could happen that the fraction of produced results keeps high within a long period $I_1$ and keeps low within the following long period $I_2$, but the overall fraction of produced results within $I_1 + I_2$ still looks good. This may be undesirable for applications that favor continuous high result quality. With a period-based recall definition, the above described situation is detectable if the length of the period is set small. In this regard, a period-based recall is indeed a stricter quality metric compared to a full-history-based recall. Using the period-based recall definition, we can guide our disorder handling approach to provide a continuous high quality.

Formally, given a user-specified result-quality measurement period $P$, we denote the recall of MSWJ results measured at any time with respect to $P$ by $\gamma(P)$, and define it as $\gamma(P) = \# \text{ results whose } ts \text{ are within the last } P \text{ time units}. \# \text{ true results whose } ts \text{ are within the last } P \text{ time units}$.

To support quality-driven disorder handling, we allow a user to specify his requirement on the minimum achieved recall $\gamma(P)$. We denote this requirement by $\Gamma$.

III. QUALITY-DRIVEN DISORDER HANDLING FRAMEWORK

We assume that there are no special tuples such as punctuations [15] or watermarks [22] in input streams to explicitly indicate the progress of a stream with respect to the tuple timestamp, which is indeed the common case in real-world scenarios. Hence, we adopt the buffer-based disorder handling approach. However, in contrast to existing buffer-based approaches, we do not aim at maximizing the result quality, i.e., $\gamma(P)$. Instead, our objective is to provide a user-configurable result-latency vs. result-quality tradeoff, by allowing a user to specify his requirement $\gamma$ on the minimum achieved recall. We then try to minimize the buffer-size, thus the result latency, under this user-specified recall requirement. In this section, we give an overview of our solution. Important notations are summarized in Table I.

A. Overview

Fig. 2 describes the overall design of our quality-driven disorder handling framework for MSWJs. For the moment, let us assume an MJoin-style [5] join implementation, where the join operation is conducted by a single join operator which takes $m$ input streams directly, rather than by a tree of binary join operators. We discuss how to relax this assumption in Sec. V. In general, we follow a two-step, prior-operation disorder handling approach, i.e., handling first the intra-stream disorder and then the inter-stream disorder within input streams before presenting them to the join operator.

For each input stream, we use the $K$-slack algorithm [12], [23] to handle its intra-stream disorder. The basic idea of
K-slack is as follows: Taking stream \( S_i \) \((i \in [1, m])\) as an example, a buffer of \( K_i \) time units is used to sort tuples from \( S_i \). Each time the local current time \( T_i \) of \( S_i \) (cf. Sec. II-A) is updated by a newly arrived tuple, every tuple \( e_i \) in the buffer that satisfies the condition \( e_i, ts + K_i \leq T_i \) is emitted. All such tuples are emitted in the timestamp order. An example of disorder handling using K-slack, where \( K_i = 1 \), is given in Fig. 3. According to the definition of the delay of a tuple (cf. Sec. II-A), the delay in each K-slack component \( \Gamma \) plays a critical role in our analytical model for estimating the recall requirement \( L \). In the current scope of the window on each stream has been discussed in existing work like [24], here, each input stream of the Synchronizer could still contain out-of-order tuples. As a result, a tuple \( e_i \) arrives at the Synchronizer can be processed in two different ways. If \( e_i \) is still inserted into the buffer, and every tuple that has the smallest timestamp is emitted from the buffer, as long as the buffer contains at least one tuple from each input stream (lines 4–8); otherwise, the tuple \( e_i \) is emitted immediately (lines 9–10).

The output stream of the Synchronizer is then processed by the MSWJ operator, whose basic idea is described in Alg. 2. Because of lines 9–10 in Alg. 1, the input to the join operator still contains out-of-order tuples. The join operator can detect these out-of-order tuples by using a variable \( \kappa T \) to track the maximum timestamp among already received tuples. A received tuple \( e_i \) is out of order if \( e_i, ts < \kappa T \). For each received tuple \( e_i \), if \( e_i \) is an in-order tuple, then \( \kappa T \) is updated if needed, and \( e_i \) is processed following a three-step procedure: (i) Invalidate expired tuples in windows on all other streams (lines 5–6); (ii) Join \( e_i \) with remaining tuples in all other windows, and produce result tuples based on the given join condition (line 7). The timestamp assigned to each result tuple is \( e_i, ts \), (iii) Insert \( e_i \) into the window on \( S_i \) (line 8). If the received tuple \( e_i \) is an out-of-order tuple, then steps (i) and (ii) are skipped; hence, a fraction of result tuples that can be derived from \( e_i \) are lost. However, if \( e_i \) still falls into the current scope of the window on \( S_i \) (i.e., \( e_i, ts \geq \kappa T - W_j \)), then \( e_i \) could still contribute to deriving future result tuples. Hence, in this case, \( e_i \) is still inserted into the window on \( S_i \) (lines 9–10). Finally, the join operator invokes the Tuple-Productivity Profiler to record the productivity of \( e_i \). The productivity of an out-of-order tuple is estimated based on past join results (cf. Sec. IV-B).

### Algorithm 1: MSWJ execution over the output of the Synchronizer

1: \( \kappa T \leftarrow 0 \)
2: for each tuple \( e_i \) \((i \in [1, m])\) arrived at the join operator do
3: \( \kappa T \leftarrow \max(e_i, ts) \)
4: for each tuple \( e_i \) arrived at the Synchronizer do
5: \( \kappa T \leftarrow \min(e_i, ts) \)
6: for window on each stream \( S_j \) \((j \neq i)\) do
7: \( \kappa T \leftarrow \min(e_i, ts) \leftarrow \min(e_i, ts) \) from SyncBuf
8: Insert \( e_i \) into the window on \( S_i \)
9: Insert \( e_i \) into the window on \( S_i \)
10: Insert \( e_i \) into the window on \( S_i \)
11: Insert \( e_i \) into the window on \( S_i \)

### Algorithm 2: Tuple-Productivity Profiler

1: Compute \( \kappa T \) for each received tuple \( e_i \) and produce result tuples based on the join condition (cf. Sec. IV-B).
2: for each tuple \( e_i \) \((i \in [1, m])\) do
3: if \( e_i, ts \geq \kappa T \) then
4: for window on each stream \( S_j \) \((j \neq i)\) do
5: \( \kappa T \leftarrow \min(e_i, ts) \)
6: for each received tuple \( e_i \) do
7: \( \kappa T \leftarrow \min(e_i, ts) \leftarrow \min(e_i, ts) \) from SyncBuf
8: Insert \( e_i \) into the window on \( S_i \)
9: Insert \( e_i \) into the window on \( S_i \)
10: Insert \( e_i \) into the window on \( S_i \)
11: Insert \( e_i \) into the window on \( S_i \)

### Algorithm 3: Statistics Monitor

1: \( \Gamma \leftarrow \Gamma \leftarrow \Gamma \)
2: for each tuple \( e_i \) \((i \in [1, m])\) do
3: if \( e_i, ts \geq \kappa T \) then
4: for each window on each stream \( S_j \) \((j \neq i)\) do
5: \( \kappa T \leftarrow \min(e_i, ts) \)
6: for each received tuple \( e_i \) do
7: \( \kappa T \leftarrow \min(e_i, ts) \leftarrow \min(e_i, ts) \) from SyncBuf
8: Insert \( e_i \) into the window on \( S_i \)
9: Insert \( e_i \) into the window on \( S_i \)
10: Insert \( e_i \) into the window on \( S_i \)
11: Insert \( e_i \) into the window on \( S_i \)
Theorem 1. With a two-step, buffer-based, prior-operation disorder handling approach (i.e., intra-stream disorder handling followed by inter-stream disorder handling before the join operation), for any buffer size configuration of the intra-stream disorder handling components (i.e., the K-slate components), where \( K_1 = k_1, K_2 = k_2, \ldots, K_m = k_m \) (\( k_i \) is a constant and \( k_i \geq 0 \)), the overall effect of the disorder handling under this configuration, and thus the produced join output, is the same as that under the configuration \( K_1 = k_2 = \cdots = K_m = k \), where \( k = \min \{|T| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \} \).

Basically, Theorem 1 says that, independent of the intra-stream disorder characteristics within the input streams, we could always find a configuration \( C \) where all K-slate components in the framework apply the same buffer size, to replace another configuration \( C' \) where the K-slate components apply different buffer sizes, such that the join output produced under \( C \) is the same as that produced under \( C' \). Hence, it suffices to use the same value of \( K \) in all K-slate components. In the following, we first illustratively show that Theorem 1 is true for 2-way joins, and then prove it for general \( m \)-way joins.

Assume a 2-way join with input streams \( S_1 \) and \( S_2 \), whose progress with respect to the tuple timestamp is as shown in Fig. 4a. \( S_1 \) is leading in terms of the timestamp progress whereas \( S_2 \) is lagging. It is important to note that, with Alg. 1, even if we do not handle the intra-stream disorder using K-slate components, i.e., \( K_1 = K_2 = 0 \), the Synchronizer would handle it, at least partially, for the leading stream. According to Alg. 1, we can deduce that, for \( S_1 \) and \( S_2 \) in Fig. 4a, the variable \( T_{\text{sync}} \) in Alg. 1 equals \( 2T \); all so-far-arrived \( S_1 \) tuples, whose timestamps are within \( (T_{\text{sync}}, T) \), are kept in and sorted by the synchronization buffer. Hence, the intra-stream disorder of \( S_1 \) is implicitly handled by a buffer of \( 1T - T_{\text{sync}} = 1T - 2T \) time units. We denote this implicit buffer size within the Synchronizer that contributes to handling the intra-stream disorder of a stream \( S_i \) by \( K_{\text{sync}}^{\text{i}} \).

Assume that the K-slate components are configured with \( K_1 = k_1 \) and \( K_2 = k_2 \), and at least one of \( k_1 \) and \( k_2 \) is not zero. Then there are two possible cases:

- **Case 1:** \( S_1 \) remains leading after K-slate (Fig. 4b). For stream \( S_2 \), the total buffer size for handling its intra-stream disorder is \( k_2 \). For stream \( S_1 \), in addition to the K-slate buffer, the synchronization buffer can further handle its intra-stream disorder, and \( K_{\text{sync}}^{\text{i}} = (1T - k_1) - (2T - k_2) \).

- **Case 2:** \( S_2 \) becomes leading after K-slate (Fig. 4c). In this case, the synchronization buffer keeps and sorts tuples from \( S_2 \) and \( K_{\text{sync}}^{\text{i}} = 0 \). \( K_{\text{sync}}^{\text{i}} = (1T - k_2) - (1T - k_1) \). The total buffer size for handling intra-stream disorder is \( k_1 \) for \( S_1 \), and \( k_2 + K_{\text{sync}}^{\text{i}} = 2T - 1T + k_1 \) for \( S_2 \). Let \( k = 2T - 1T + k_1 \). Compared to the case in Fig. 4a, the total buffer size for handling the intra-stream disorder is increased by \( k \) for both streams, which is equivalent to having a configuration \( K_1 = K_2 = k \).

We now prove Theorem 1 for general MSWIs:

**Proof:** The nature of Alg. 1 determines that the variable \( T_{\text{sync}} \) always equals to the maximum timestamp among tuples in the slowest stream produced by the K-slate components, where the meaning of “slow” was defined in Sec. II-A. If all K-slate components are configured with a buffer of size 0, then \( T_{\text{sync}}^{\text{i}} = \min \{|T| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \} \), and \( K_{\text{sync}}^{\text{i}} \) for each stream \( S_i \) can be determined as \( K_{\text{sync}}^{\text{i}} = T - T_{\text{sync}}^{\text{i}} = T - \min \{|T| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \} \). \( K_{\text{sync}}^{\text{i}} \) is also the total buffer size for handling the intra-stream disorder of \( S_i \) under this configuration. If the configuration for the K-slate components is \( K_1 = k_1, K_2 = k_2, \ldots, K_m = k_m (k_i > 0) \), then \( T_{\text{sync}}^{\text{i}} = \min \{|T - k_i| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \}, \text{ and } K_{\text{sync}}^{\text{i}} = (1T - k_i) - T_{\text{sync}}^{\text{i}} = T - k_i - \min \{|T - k_i| i \in [1, m] \}. \) Now the total buffer size for handling the intra-stream disorder of \( S_i \) is \( k_1 + K_{\text{sync}}^{\text{i}} = T - \min \{|T - k_i| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \}. \) Compared to the case where \( K_i = 0 \) for all \( i \in [1, m] \), for each stream, the total buffer size for handling its intra-stream disorder is increased by \( (1T - \min \{|T - k_i| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \} - (1T - \min \{|T - k_i| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \} = \min \{|T| i \in [1, m]| \min \{|T - k_i| i \in [1, m] \} \}. \) Hence, it is equivalent to having a configuration \( K_1 = K_2 = \ldots = K_m = \min \{|T| i \in [1, m]| \min \{|T - k_i| i \in [1, m]| \} \} \).

The Same-K policy has another important benefit:

**Proposition 1.** With the Same-K policy, for any two input streams \( S_i \) and \( S_j \), the time skew (cf. Sec. II-A) between their corresponding K-slate output streams is the same as the time skew between \( S_i \) and \( S_j \).

**Proof:** \( \forall i, j \in [1, m], \forall k, |(1T - k) - (1T - k)| = |T - j| \). From the discussion above, we can see that \( K_{\text{sync}}^{\text{i}} \) for any stream is essentially the time skew between its corresponding K-slate output stream and the slowest output stream among all K-slate components. Proposition 1 suggests that, with the Same-K policy, we can determine \( K_{\text{sync}}^{\text{i}} \) directly based on time skews among all raw input streams, regardless of the specific value of \( K \) chosen for the K-slate components. We use the Statistics Manager in Fig. 2 to monitor \( K_{\text{sync}}^{\text{i}} \) at runtime.

IV. MODEL-BASED BUFFER-SIZE ADAPTATION

Thanks to the Same-K policy introduced in Sec. III-B, at each adaptation step, the Buffer-Size Manager only needs to determine a common \( K \) value for all K-slate components in the framework. Recall that the objective is to find the minimum possible \( K \) value to meet the user-specified result-quality (i.e., recall) requirement. To this end, in this section, we propose a model-based approach.

Specifically, at each adaptation step, we analytically model the recall of the join results that would be produced in the next adaptation interval, whose length is \( L \), as a function
Algorithm 3 Model-based $K$ Adaptation

Input:
System parameters:
$L$ - Adaptation interval applied in the Buffer-Size Manager
$b$ - Size of a basic window
$g$ - $K$-search granularity

Runtime statistics:
Tuple-delay statistics maintained by Statistics Manager
Tuple-productivity statistics maintained by Tuple-Productivity Profiler
Result-size statistics maintained by Result-Size Monitor

Output: $k^*$ ($K$-slack buffer size applied in the next adaptation interval)

1: $MaxD^H \leftarrow$ current maximum tuple delay
2: $\Gamma' \leftarrow$ instant recall requirement derived from $\Gamma$
3: $k^* \leftarrow 0$
4: while ($k^* \leq MaxD^H \land \gamma(L, k^*) < \Gamma'$) do
5: $k^* \leftarrow k^* + g$
6: return $k^*$

Algorithm 3 Statistics Manager

We then search for the minimum possible value of $K$ such that $\gamma(L, K) \geq \Gamma'$ holds. We denote this $K$ value by $k^*$. Alg. 3 describes the main algorithm for finding $k^*$ for the next adaptation interval. Currently, we search for $k^*$ using a trial and error method. Specifically, let $MaxD^H$ denote the current maximum tuple delay within a recent history of input streams that is monitored by the Statistics Manager. We examine $k^* = 0, k^* = g, k^* = 2g, k^* = 3g, \ldots$ ($g > 0$), until either $k^* > MaxD^H$ or $\gamma(L, k^*) \geq \Gamma'$; the parameter $g$ is referred to as the $K$-search granularity. Studying other algorithms for searching for $k^*$ is a topic of future work.

In the following, we give a detailed description of how $\gamma(L, K)$ is computed on each iteration in Alg. 3 in Sec. IV-A and Sec. IV-B, and describe how $\Gamma'$ is derived in Sec. IV-C.

A. Modeling $\gamma(L, K)$

To estimate the recall within $L$ time units under a certain value of $K$, we need to estimate the result size that would be produced within $L$ under $K$, denoted by $N_{prod}(L, K)$, and the true result size within $L$, denoted by $N_{true}(L)$, if input streams are in order and synchronized with each other. $N_{true}(L)$ is independent of the setting of $K$.

Estimating $N_{true}^\infty(L)$. For an MSWJ with an arbitrary join condition $p^\infty$, $N_{true}^\infty(L)$ can be estimated by multiplying the result size of the corresponding cross-join, denoted by $N_{true}^\infty(L)$, with the selectivity of the join condition, denoted by $sel^\infty$. We defer the discussion of estimating $sel^\infty$ to Sec. IV-B. For the moment, let us assume that $sel^\infty$ is known. $N_{true}^\infty(L)$ is the sum of the number of cross-join results that would be produced at the arrival of each tuple $e_i$ ($i \in [1, m]$) during $L$ when input streams present no disorder. The number of cross-join results produced at the arrival of $e_i$ is a simple product of the number of tuples within the current window on every other stream $S_j$ ($j \neq i$). Let $S_i[W_i]$ denote the set of tuples that are within the current window on stream $S_i$, and $|S_i[W_i]|$ denote its cardinality. $|S_i[W_i]|$ can be estimated based on the average data arrival rate of $S_i$, denoted by $r_i$, and the window size $W_i$, i.e., $|S_i[W_i]| = r_i \cdot W_i$. For each stream $S_i$, the total number of tuples that would arrive during $L$ can be estimated based on $r_i$ as well, as $r_i \cdot L$. In summary, we estimate $N_{true}^\infty(L)$ as

$$N_{true}^\infty(L) = sel^\infty \cdot N_{true}^\infty(L) = sel^\infty \cdot \sum_{i=1}^{m} (r_i \cdot L \cdot \prod_{j=1, j \neq i} W_j)$$

Estimating $N_{prod}^\infty(L, K)$. We estimate $N_{prod}^\infty(L, K)$ again based on the result size of the corresponding cross-join under $K$, denoted by $N_{prod}^\infty(L, K)$, and the join selectivity under $K$, denoted by $sel^\infty(K)$. We estimate $N_{prod}^\infty(L, K)$ based on the following observations: (1) The join operator produces result tuples, if any, only at the arrival of in-order tuples (cf. Alg. 2). (2) When an in-order tuple $e_i$ arrives at the join operator, $S_j[W_j]$ ($j \neq i$) may be incomplete, because some tuples $e_j$ that satisfy $e_j, ts \geq e_i, ts - W_j$ may have not arrived because of the incomplete sorting by the $K$-slack components and the Synchronizer. We refer to such a tuple as a missing tuple of $S_j[W_j]$. (3) If we divide a window into small segments, then a recent segment of a window (i.e., a segment whose scope is closer to $e_i, ts$) often has more missing tuples than an older segment of the window. The reason is that, by the time $e_i$ arrives, out-of-order tuples whose timestamps fall into the scope of an older segment of a window might have already arrived at the join operator, and been inserted into the window (lines 9–10 in Alg. 2); whereas out-of-order tuples whose timestamps fall into the scope of a recent segment of the window can be observed only at later points in time.

These observations suggest that, to estimate $N_{prod}^\infty(L, K)$, we need to estimate, under the given setting of $K$, the number of in-order tuples that the join operator would receive during $L$, and the degree of completeness of $S_j[W_j]$ ($j \neq i$) at the arrival of an in-order tuple $e_i$ ($i \in [1, m]$). To this end, we introduce a discrete random variable $D_i$ for each input stream $S_i$ to represent the coarse-grained delay of a tuple $e_i$ in $S_i$. Specifically, $D_i$ takes the value 0 if $delay(e_i) = 0$, the value 1 if $delay(e_i) \in (0, g]$, the value 2 if $delay(e_i) \in (g, 2g]$, and so forth; namely, the granularity for non-zero tuple delays is the same as the $K$-search granularity in Alg 3. Let $f_{D_i}$ denote the probability density function (pdf) of $D_i$, i.e., $f_{D_i}(d) = Pr[D_i = d]$, where $d \in \{0, 1, 2, \ldots \}$. Based on the assumption that the near future resembles the recent past, for each input stream $S_i$, the Statistics Manager monitors delays of input tuples that are within a window $R_{stat}^{dist}$ over $S_i$’s recent history, and approximates $f_{D_i}$ using a histogram $H_i$. A fixed size for $R_{stat}^{dist}$ is hard to define without a priori knowledge of the disorder pattern within the stream, and is also sensitive to changes in the disorder pattern. Hence, in this work, we use the adaptive window approach proposed in [25] to dynamically adjust the size of $R_{stat}^{dist}$, based on the rate of changes detected from the delays of tuples in $R_{stat}^{dist}$ itself. The size of each $R_{stat}^{dist}$ ($i \in [1, m]$) is adjusted separately.

$f_{D_i}$ captures the tuple-delay characteristics within a raw input stream $S_i$. After the intra-stream disorder handling by the $K$-slack component, and the inter-stream disorder handling by the Synchronizer, the tuple-delay characteristics in the stream received by the join operator is different from $f_{D_i}$. Let $D^K$ denote a discrete random variable representing the coarse-grained delay of a tuple in the corresponding stream.
of $S_i$ that is received by the join operator under a certain $K$ setting. Let $f_{DK}$ represent the pdf of $D^K$. We can capture the change from $f_{D_i}$ to $f_{DK}$ based on the observation that, for any tuple $e_i$ in a raw input stream $S_i$, the delay of $e_i$ within the corresponding stream received by the join operator changes from $delay(e_i)$ to $delay^K(e_i)$, where $delay^K(e_i) = max(0, delay(e_i) - K - K_{sync}^K)$. Hence, we can derive $f_{DK}$ from $f_{D_i}$ using Eq. (2).

$$f_{DK}(d) = \begin{cases} \frac{(K + K_{sync}^K)}{\theta} f_{D_i}(d'), & d = 0 \\ f_{D_i}(d + K + K_{sync}^K), & d \in \{1, 2, 3, \ldots \} \end{cases}$$  

We assume that $K_{sync}^K$ for each stream keeps stable during the next adaptation interval, and estimate it as $K_{sync}^K = min\{K_{sync}^i | j = \{1, m\}\}$, where $K_{sync}^i$ represents the average of all $K_{sync}$ measurements obtained by the Statistics Manager within $B_{i,stat}$. Having estimated $K_{sync}^K$, we can then approximate $f_{DK}$ using histogram $H_i$ as well. Moreover, using $f_{DK}$, we can estimate the expected number of in-order $S_i$ tuples that would arrive at the join operator during $L$ as $r_i \cdot L \cdot f_{DK}(0)$.

To capture the difference in the degree of completeness among different segments of a window $W_i$, we borrow the notion of basic window introduced in [3], and divide each window into a stream into basic windows of $b$ time units. The window on stream $S_i$ consists of $n_i = \lfloor W_i/b \rfloor$ basic windows. Let $w_{i}^l$ denote the $l$-th, $l \in [1, n_i]$, basic window on $S_i$; $w_{i}^1$ represents the most recent basic window. At any point in time, the scope of a basic window $w_{i}^l$ on $S_i$ can be determined as $(\kappa T - l \cdot b, \kappa T - (l - 1) \cdot b)$ for $l \in [1,n_i]$; and $(\kappa T - W_i, \kappa T - (n_i - 1) \cdot b)$ for $l = n_i$.

For $w_{i}^l$, among all $S_i$ tuples $e_i$ whose timestamps fall into the scope of $w_{i}^l$, tuples having $delay^K(e_i) = 0$ should have arrived. Hence, we estimate the expected number of tuples that are included in $w_{i}^l$, denoted by $|w_{i}^l|$, as $|w_{i}^l| = r_i \cdot b \cdot f_{DK}(0)$. For $w_{i}^2$ tuples, all tuples having $delay^K(e_i) \in [0, b/4]$ should have arrived, and $|w_{i}^2|$ can be estimated as $r_i \cdot b \cdot \sum_{d=0}^{b/4} f_{DK}(d)$. In general, $|w_{i}^l|$ for any $l \in [1, n_i]$ is estimated using Eq. (3).

$$|w_{i}^l| = \begin{cases} r_i \cdot b \cdot \sum_{d=0}^{(l-1) \cdot b/4} f_{DK}(d), & l \in [1, n_i - 1] \\ r_i \cdot (W_i - (n_i - 1) \cdot b) \cdot \sum_{d=0}^{b/4} f_{DK}(d), & l = n_i \end{cases}$$

Based on estimations of $|w_{i}^l|$, we can estimate $|S_i(W_i)|$ as $\sum_{i=1}^{n_i} |w_{i}^l|$. Furthermore, $N_{\text{prod}}(L, K)$ can be estimated as

$$N_{\text{prod}}^\ast(L, K) = sel^\ast(K) \cdot \frac{m}{\bigg(\sum_{i=1}^{m} \prod_{j=1, j \neq i}^{n_i} |w_{i}^j| \bigg)} \sum_{i=1}^{m} \frac{\prod_{j=1, j \neq i}^{n_i} |w_{i}^j|}{W_j}$$

Note that a bigger value of $b$ implies a more conservative estimation of $|S_i(W_i)|$ and thus $N_{\text{prod}}(L, K)$. When $b$ is chosen such that $n_i = 1$ for all $i \in [1, m]$, it means that the estimation of $|S_i(W_i)|$ considers only in-order tuples.

Calculating $\gamma(L, K)$. Having estimated $N_{\text{true}}^\ast(L)$ and $N_{\text{prod}}^\ast(L, K)$, we can calculate $\gamma(L, K)$ as

$$\gamma(L, K) = \frac{sel^\ast(K) \cdot \sum_{i=1}^{m} \prod_{j=1, j \neq i}^{n_i} |w_{i}^j|}{\sum_{i=1}^{m} \frac{\prod_{j=1, j \neq i}^{n_i} |w_{i}^j|}{W_j}}$$

where the common factor $((\prod_{i=1}^{m} r_i) \cdot L)$ in Eq. (1) and Eq. (4) is canceled off.

B. Learning DPCorr and Estimating Join Selectivity

We now discuss how to estimate $\gamma(L, K)$ needed in Eq. (5).

A naive strategy is to assume $sel^\ast(K) = sel^\ast$, which is equivalent to estimating $\gamma(L, K)$ based on result sizes of the corresponding cross-join. We denote this strategy by EqSel. However, when stream disorder is present and the disorder handling is incomplete, the streams received by the join operator are different from the streams in the ideal case, where all input streams are in order and synchronized. As a result, the join selectivity when stream disorder is present is often also different from the join selectivity in the ideal case. For instance, for the 2-way join in Fig. 5, where tuples are represented in the same way as in Fig. 1, when the input is ideal or the disorder handling is complete, the join selectivity is $\frac{1}{2}$ (Fig. 5a). If after disorder handling, a tuple in $S_i$ arrives at the join operator out of order, then the join selectivity is no longer $\frac{1}{2}$ (Fig. 5b and 5c). Hence, it is more reasonable to assume that $sel^\ast(K)$ is different from $sel^\ast$. We denote this strategy by NonEqSel.

Stream $S_1$:
| A | B | C |
|---|---|---|
| b | b | b |

Stream $S_2$:
| A | B | C |
|---|---|---|
| b | b | b |

| arrival order at the join operator | the join selectivity |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 1 | 0 |

Fig. 5. Effect of out-of-order tuples arriving at the join operator on the join selectivity and the recall of results.

To estimate $sel^\ast(K)$ for different settings of $K$, we need to consider the correlation between the delay and the productivity of tuples, i.e., DPCorr; because, as implied by Fig. 5b and 5c, tuples with different delays do not necessarily have the same productivity, and the unsuccessful handling of an out-of-order tuple having a high productivity has a higher impact on the produced recall than the unsuccessful handling of an out-of-order tuple having a low productivity.

Extensive work (e.g., [26], [27]) exists, which uses synopsis of input streams (e.g., histograms, sketches, samples) to estimate the join result size or tuple productivities, and thereby the join selectivity. However, such input-based approaches do not work for joins with complex conditions, e.g., conditions involving user-defined functions [28]. To support arbitrary join conditions and to be able to estimate $sel^\ast(K)$ for different settings of $K$ in each adaptation step, we adopt an output-based approach; namely, we learn DPCorr by monitoring the output of the join. Such output-based approaches were also applied in prior work like [3], [20], [29] for different purposes.

Specifically, for each input tuple $e_i$ ($i \in [1, m]$), the $K$-slack component for stream $S_i$ annotates $e_i$ with $delay(e_i)$. Tuple $e_i$ carries this delay annotation through the Synchronizer. If $e_i$ arrives in order at the join operator, then during the join processing, the join operator records both the number of cross-join result size, $n^\ast(e_i)$, that $e_i$ would have, and the number of join results, $n^\ast(e_i)$, that $e_i$ actually derived, given the current window content $S_i(W_i)$ ($j \neq i$) on the other streams. The three numbers $delay(e_i)$, $n^\ast(e_i)$, and $n^\ast(e_i)$ are then provided to the Tuple-Productivity Profiler. The Tuple-Productivity Profiler uses two maps, $M^\ast$ and $M^\ast$, to maintain accumulated $n^\ast$ and $n^\ast$, respectively, for each coarse-grained tuple delay observed within the last adaptation.
interval. The applied granularity for non-zero tuple delays is again $g$, which is consistent with $K$-search granularity in Alg. 3. If $e_i$ arrives out of order at the join operator, no join processing is conducted for $e_i$. We then estimate $n^\times(e_i)$ and $n^\circ(e_i)$ as the maximum $n^\times(e)$ and $n^\circ(e)$, respectively, over all in-order tuples $e$ received in the last adaptation interval. Let $M^\times[d] / (M^\circ[d])$ represent the value to which the coarse-grained delay value $d$ is mapped in $M^\times / (M^\circ)$, $M^\times [d] = \sum_{d=0}^{K \times \max} n^\times(e) / (M^\circ [d] = \sum_{d=0}^{K \times \max} n^\circ(e))$. Assuming that the join selectivity in the next adaptation interval is the same as the join selectivity in the last adaptation interval, for each $K$ value examined in Alg. 3, we estimate $sel^\times(K)$ as $(\sum_{d=0}^{K \times \max} M^\times [d]) / (\sum_{d=0}^{K \times \max} M^\circ [d])$.

The estimation of $sel^\times(K)$—the true join selectivity within $L$ when input streams present no disorder—is based on the following observation: For the join operator, the case where raw input streams present no disorder is equivalent to the case where input streams present disorder but the disorder is handled completely by using large-enough $K$-slack buffers. The join selectivities in both cases are the same. Therefore, we estimate $sel^\times(K)$ as $(\sum_{d=0}^{MaxDM} M^\times [d]) / (\sum_{d=0}^{MaxDM} M^\circ [d])$, where $MaxDM$ represents the current maximum tuple delay in $M^\times$ (or $M^\circ$); because with a buffer of size $MaxDM$, any tuple $e$ having $delay(e) \leq MaxDM$ can be reordered correctly (cf. Sec. III-A). In summary, the estimation for $sel^\times(K)$ is

$$sel^\times(K) = \frac{\sum_{d=0}^{K \times \max} M^\times [d]}{\sum_{d=0}^{K \times \max} M^\circ [d]} \times \frac{\sum_{d=0}^{MaxDM} M^\times [d]}{\sum_{d=0}^{MaxDM} M^\circ [d]}.$$  \hspace{1cm} (6)

C. Deriving the Instant Recall Requirement

We now describe how the instant recall requirement $\Gamma$ needed in Alg. 3 is derived. This is done with the help of the runtime statistics maintained by the Tuple-Productivity Profiler and the Result-Size Monitor in Fig. 2.

Given the user-specified result-quality measurement period $P$, the Result-Size Monitor maintains the number of join results produced within the last $P - L$ time units, denoted by $N^\times_{prod}(P - L)$. Let $N^\times_{true}(P - L)$ denote the number of true join results within the last $P - L$ time units if input streams present no disorder. In general, to make the recall measured over $P$ at the end of the next adaptation interval meet the user-specified requirement $\Gamma$, the recall measured over the next adaptation interval, i.e., $\Gamma'$, should satisfy Eq. (7).

$$\frac{N^\times_{prod}(P - L) + N^\times_{true}(P - L)}{N^\times_{true}(P - L) + N^\times_{true}(P - L)} \geq \Gamma'$$  \hspace{1cm} (7)

Recall that we can estimate $N^\times_{true}(P - L)$ by $\sum_{d=0}^{MaxDM} M^\times [d]$, where $M^\times$ maintains accumulated tuple productivities within the last adaptation interval. Furthermore, $N^\times_{true}(P - L)$ can be estimated by summing up the $N^\times_{true}(L)$ estimations obtained in the last $(P - L)/L$ adaptation intervals. Together with $N^\times_{prod}(P - L)$ maintained by the Result-Size Monitor, we can derive $\Gamma'$ from Eq. (7). The final instant recall requirement applied in Alg. 3 is $max(\Gamma', 1)$.

V. APPLICABILITY IN DISTRIBUTED MSWJ PROCESSING

MSWJs are by nature CPU and memory intensive. To support high volume input data, big window sizes, and expensive join conditions, scalable and distributed MSWJ processing has gained a lot of research interest recently (e.g., [6, 30]). An MSWJ can be implemented as either a single MJoin-style operator or a tree of binary join operators. Both types of implementation support distributed processing by splitting a macro $m$-way or binary join operator into smaller operator instances, exploiting pipelined and data parallelism.

As long as each operator instance follows the same processing semantics as in Alg. 2, then regardless of the specific implementation type, we can adapt the quality-driven disorder handling approach described in this paper to apply it in a distributed setup in the following way: Same as in Fig. 2, we use $K$-slack components to handle the intra-stream disorder of all input streams, and adjust the value of $K$ adaptively using the Buffer-Size Manager. Each input stream to an operator instance in the distributed setup is either the output stream of a $K$-slack component, or the output stream of another operator instance. To deal with the inter-stream disorder among inputs, each operator instance is associated with a Synchronizer. Indeed, such a prior-join synchronization strategy was already applied in existing distributed join systems such as [6, 30].

Key information that the Buffer-Size Manager requires to make adaptation decisions include $f_{D}$, $K^*_{true}$, $M^\times$, $M^\circ$, and $N^\times_{true}(P - L)$; all other information can then be derived. We can obtain $f_{D}$, $K^*_{true}$ by monitoring the raw input streams, and $N^\times_{true}(P - L)$ by monitoring the final join output. To obtain $M^\times$, each operator instance needs to be instrumented so that, when receiving a tuple $e$ from a $K$-slack component, it annotates each intermediate result tuple produced at the arrival of $e$ with $delay(e)$; and when receiving such an annotated intermediate result tuple, it further propagates the tuple-delay annotation to each produced (intermediate) result tuple. Then $M^\times$ can be built by monitoring the final join output. To build $M^\circ$ accurately, for each $K$-slack output tuple $e_i$ ($i \in [1, m]$) that triggers the join processing at an operator instance, we need to know $|S_j| W_j|$ for all $j (j \neq i)$. However, each $S_j W_j$ is often split into slices, which are maintained by different operator instances. Hence, obtaining accurate $|S_j| W_j|$ would require communicating with all involved operator instances, which can be expensive. An alternative is to approximate each $|S_j| W_j|$ using the average data rate $r_i$ monitored by the Statistics Manager and the window size $W_j$.

VI. EXPERIMENTS

We implemented the proposed model-based, adaptive, quality-driven disorder handling approach in a prototypical version of SAP ESP [31]. In this section, we evaluate the effectiveness of our approach for varying user-specified requirements, and study effects of important system parameters. All experiments were conducted on a HP Z620 workstation, which has 24 cores (2.9GHz per core) and 96 GB RAM.

Datasets and Queries. For the evaluation, we used one real-world and two synthetic datasets with two, three, and four input streams. A different join query was used for each dataset.

- The real-world soccer-game dataset $D^{soc}_{real}$ consists of two streams ($s_1$ and $s_2$) of player-position data, which was collected by sensors during a 23-minute soccer training game, one stream for each team [1]. We projected each original stream onto $(ts, sID, xCoord, yCoord)$, where $sID$ identifies players and the pair of coordinates $(xCoord, yCoord)$ encodes positions in the field. Each stream contains approximately 450k tuples. The maximum tuple delay is 22 seconds in $s_1$ and 26 seconds in $s_2$. The join query $Q^{soc}_{real}$ evaluated on $D^{soc}_{real}$ is to find all occurrences, within a 6The output of an operator instance is guaranteed to contain no intra-stream disorder because of the applied processing semantics.
5-second sliding window, when the distance between two players, one from each team, is shorter than 5 meters. A custom function dist() calculates the distance and is the join condition for this scenario.

\[ Q^{x^2} \] SELECT * FROM S; [5 SEC], S2; [5 SEC] WHERE dist(S1.xCoord, S1.yCoord, S2.xCoord, S2.yCoord) < 5

- The first synthetic dataset \( D_{syn}^{x^3} \) consists of three streams, which have the same schema \((ts, a1)\). All streams start from a common timestamp \( ts_{syn} \), which has millisecond (ms) granularity, and cover an interval of 30 minutes. For each stream \( S_i \) (\( i \in \{1, 3\} \)), tuples were generated sequentially as follows. Let \( T' = ts_{syn} \) initially. For each new tuple \( e \), we increased \( T' \) by 10 ms (i.e., \( T' = T' + 10 \)), and chose a random delay \( delay(e) \) from \([0, 20.0]\) seconds using a Zipf distribution with skew \( z_i^0 \). We then set \( e.ts \) to \( T' \) if \( delay(e) = 0 \), or to \( T' - delay(e) \) otherwise. By increasing \( T' \) by 10 ms first for each newly generated tuple, we simulated a data rate of 100 tuples/sec. The applied Zipf skew \( z_i^0 \) for all streams were \( z_i^0 = 2.0 \) and \( z_i^1 = z_i^2 = 3.0 \). The value of \( a1 \) for \( e \) was generated randomly from the integer interval \([1, 100]\) using a Zipf distribution as well.

- The second synthetic dataset \( D_{syn}^{x^4} \) consists of four streams, whose schemas are \( S_1: (ts, a1, a2, a3) \), \( S_2: (ts, a1, a2) \), \( S_3: (ts, a2) \), and \( S_4: (ts, a3) \). Timestamps and attribute values were generated in the same way and from the same domains as in \( D_{syn}^{x^3} \). The Zipf skew used for generating each attribute was also initialized with 1.0. Zipf skews used for generating tuple delays were \( z_i^0 = z_i^1 = z_i^2 = 3.0 \) and \( z_i^3 = 4.0 \). A 4-way join query was evaluated on \( D_{syn}^{x^4} \):

\[ Q^{x^4}; SELECT * FROM S; [5 SEC], S2; [5 SEC], S3; [5 SEC], S4; [5 SEC] WHERE S1.a1=S2.a1 AND S1.a1=S2.a1 AND S2.a2=S3.a2 AND S3.a3=S4.a3 \]

For each dataset, we generated a sorted version where tuples of all streams are globally ordered according to their timestamps. By evaluating \( Q^{x^2} \) \((x \in \{2, 3, 4\})\) on the corresponding sorted dataset, we can obtain the true join results therewith calculating the recall of results produced for the unsorted dataset.

Default Parameter Configuration. Unless otherwise stated, we used the following parameter configuration in our experiments: quality measurement period \( P = 1 \text{ min} \), basic window size \( b = 10 \text{ ms} \), K-search granularity \( g = 10 \text{ ms} \), and adaptation interval \( L = 1 \text{ sec} \).

Metrics. We consider the following metrics to evaluate our quality-driven disorder handling approach:

- The average buffer size in a K-slack component. Recall that all K-slack components share the same buffer size at any point in time (cf. Sec. III-B). The smaller the average K-slack buffer size, the lower the average result latency.

- The percentage of recall measurements \( \gamma(P) \) that fulfill the user-specified recall requirement \( \Gamma \)—in short, the req. fulfillment pct. We denote this metric by \( \Phi(\Gamma) \):

\[ \Phi(\Gamma) = \# \gamma(P) \text{ measurements that are not lower than } \Gamma \] 

\[ \# \gamma(P) \text{ measurements} \]

\( \gamma(P) \) of join results produced under disorder handling was measured right before each adaptation of \( K \). Recall measurements obtained during the first quality measurement period \( P \) were excluded when computing \( \Phi(\Gamma) \).

Baseline Disorder Handling Approaches. We consider two alternative Buffer-Size Manager (cf. Fig. 2) implementations as baselines, which manage buffer sizes in K-slack components in two extreme ways: (1) No-K-slack, which does not handle the intra-stream disorder of each stream via K-slack, i.e., \( K_i = 0 \) for all \( i \in \{1, m\} \), (2) Max-K-slack, which updates the value of \( K \) in each K-slack component dynamically to be equal to the maximum delay among so-far-observed tuples from all streams [12].

A. Results of Baseline Disorder Handling Approaches

Fig. 6 shows recalls of join results \( \gamma(P) \) produced by No-K-slack for each dataset, using default settings of \( P \) and \( L \). For \( (D_{syn}^{x^2}, Q^{x^2}) \), the measured recall is only around 0.5 most of the time. The overall recall for \( (D_{syn}^{x^4}, Q^{x^4}) \) is the highest, but is only around 0.8, which is still a low result-quality for many applications. Fig. 6 implies that, to obtain a high result quality, doing inter-stream disorder handling only is not sufficient and intra-stream disorder handling is necessary.

| \( \Gamma \) | \( (D_{syn}^{x^2}, Q^{x^2}) \) | \( (D_{syn}^{x^4}, Q^{x^4}) \) | \( (D_{syn}^{x^3}, Q^{x^3}) \) |
|---|---|---|---|
| Avg. \( K \) (sec) | 19.96 | 19.72 | 13.88 |
| Avg. \( \gamma(P) \) | 1.0 | \( \approx 0.999 \) | \( \approx 0.999 \) |

The average of \( K \) and \( \gamma(P) \) produced by Max-K-slack are listed in Table II. The average of \( K \) for \( (D_{syn}^{x^2}, Q^{x^2}) \) is different from that for \( (D_{syn}^{x^4}, Q^{x^4}) \), because tuples with large delays appear later in streams of \( D_{syn}^{x^4} \) than in streams of \( D_{syn}^{x^3} \). The average \( \gamma(P) \) is not always 1, because Max-K-slack does not guarantee complete disorder handling; each increase of \( K \) in Max-K-slack is triggered by an out-of-order tuple \( e \) whose delay is larger than the current \( K \) value, and hence \( e \) is still an out-of-order tuple in the output stream of K-slack.

Fig. 6 and Table II together corroborate that there is an inevitable tradeoff between the result latency and the result quality in disorder handling.

B. Effectiveness Results

Varying user-specified recall requirements. We first studied the effectiveness of our approach under varying user-specified recall requirements \( \Gamma \) for each pair of dataset and join query. Recall that our approach is based on an analytical model of \( \gamma(L, K) \), which uses statistics collected from past data to make predictions about future data (cf. Sec. IV). Due to the dynamic nature of data streams, it is impossible to make precise predictions; as a result, the derived buffer sizes may not guarantee a \( \Phi(\Gamma) \) of 100%. However, a produced \( \gamma(P) \) that violates \( \Gamma \) can be indeed very close to \( \Gamma \), and is acceptable in most scenarios. Hence, in addition to \( \Phi(\Gamma) \), we also measured \( \Phi(\approx 0.999) \), namely, the percentage of \( \gamma(P) \) measurements that
are not lower than $\Gamma$ by 1%. In this experiment, we also compared the two modeling strategies—EqSel and NonEqSel—that were discussed in Sec. IV-B.

Fig. 7 shows the experimental results. For ease of comparison, we included the average $K$ produced by Max-K-slack for each dataset in the corresponding sub-figure. We can see that, for both EqSel and NonEqSel, the average $K$ goes up as $\Gamma$ increases, which again reveals the result-latency vs. result-quality tradeoff. NonEqSel produces a bit higher average $K$ than EqSel; the $\Phi(\Gamma)$ and $\Phi(0.99\Gamma)$ produced by NonEqSel are not much higher than those produced by EqSel for $(D_{\text{real}}^{x2}, Q^{x2})$ and $(D_{\text{syn}}^{x3}, Q^{x3})$, but are significantly higher for $(D_{\text{syn}}^{x3}, Q^{x3})$. For each examined dataset/query pair, NonEqSel achieves a $\Phi(0.99\Gamma)$ of at least 97% for all examined values of $\Gamma$. Hence, NonEqSel is more robust than EqSel towards different datasets and join queries, and is used in all following experiments.

Compared to the state-of-the-art approach Max-K-slack, our approach, using NonEqSel, can significantly reduce the average $K$, thus the result latency incurred by disorder handling, while still honoring the user-specified result-quality requirement. For instance, even for a high recall requirement $\Gamma = 0.99$, the average $K$ is reduced by more than 95% for $(D_{\text{real}}^{x2}, Q^{x2})$. For an even higher recall requirement $\Gamma = 0.999$, our approach still achieves a 35% reduction in the average $K$ for $(D_{\text{real}}^{x2}, Q^{x2})$, and reduces to the Max-K-slack approach for the other two datasets.

**Varying user-specified result-quality measurement periods.**

We further studied the effectiveness of our approach under varying user-specified result-quality measurement periods $P$. Fig. 8 shows the results for $(D_{\text{real}}^{x2}, Q^{x2})$ and $(D_{\text{syn}}^{x3}, Q^{x3})$ under $\Gamma = 0.95$ and $\Gamma = 0.99$, although we observed similar results for $(D_{\text{syn}}^{x3}, Q^{x3})$ and other $\Gamma$ values. The other parameters took default values.

As expected, it is more difficult to obtain a high $\Phi(\Gamma)$ and $\Phi(0.99\Gamma)$ for small values of $P$ than for big values of $P$; because the smaller the value of $P$, the smaller the chance that a low recall of join results produced within one adaptation interval gets compensated by recalls produced in other adaptation intervals within the same measurement period. Nevertheless, we still achieve a $\Phi(0.99\Gamma)$ of more than 90% for all examined values of $P$.

**C. Effect of the Adaptation Interval System Parameter**

Fig. 9 studies the effect of the adaptation interval $L$ on the performance of our approach. Where $L$ is varied from 0.1 to 10 seconds. The figure reports results for $(D_{\text{seq}}^{x2}, Q^{x2})$ and $(D_{\text{syn}}^{x3}, Q^{x3})$ under $\Gamma = 0.95$ and $\Gamma = 0.99$. The other parameters took default values.

The average $K$ grows noticeably as $L$ increases. This can be explained by the selectivity estimation done in Eq. (6). Recall that we estimate the productivity of an out-of-order tuple arrived at the join operator conservatively as the maximum tuple productivity observed within the last adaptation interval. The maximum tuple productivity observed within a long interval is often higher than that observed in a short interval; hence, the estimated selectivity is smaller, which often leads to a smaller result of Eq. (6). Moreover, for longer adaptation intervals, a large value of $K$ determined in one adaptation step is also applied for a longer time. The increase
of $K$ leads to a great increase of $\Phi(\Gamma)$ for $(D^{x3}_{syn}, Q^{x3})$ under $\Gamma = 0.99$, but has little effect on the achieved result quality for the other three examined cases. We find that $L = 1$ second produces a good tradeoff between the average $K$ and the achieved result quality in our experiments.

D. Effect of the K-Search Granularity System Parameter

Recall that in each adaptation step, we search for the optimal setting of $K$ by examining possible $K$ values incrementally, starting from the value 0 (cf. Alg. 3). The search granularity is $g$. Fig. 10 studies the effect of the setting of $g$ on the performance of our approach. The value of $g$ was varied from 1 to 1000 ms. The other parameters took default values. As $g$ increases, the average $K$ increases noticeably for $(D^{x3}_{real}, Q^{x3})$, but has nearly no changes for $(D^{x3}_{syn}, Q^{x3})$. This result implies that the value of $g$ has stronger effect in scenarios where satisfying the result-quality requirement $\Gamma$ requires a small buffer size than in scenarios where satisfying $\Gamma$ requires a big buffer size. We empirically chose $g = 10$ ms as the default setting in our system.

E. Adaptation Overhead

Last, we studied the overhead of our model-based buffer size adaptation approach in terms of the time needed to find the optimal value of $K$ in an adaptation step; namely, the runtime of Alg. 3. The adaptation time is influenced by the number of input streams $m$, the user-specified recall requirement $\Gamma$, and the $K$-search granularity $g$. The number of input streams varies from 2 to 4 in our three datasets. For each dataset, we picked different combinations of $\Gamma$ and $g$ values, and ran the corresponding join query three times on that dataset for each $(\Gamma, g)$ combination. The other parameters took default values. For each $(\Gamma, g)$ combination, we recorded the average time of an adaptation step over all three runs of the query under that combination. The results are shown in Fig. 11. As expected, the adaptation time goes down as $g$ increases and $\Gamma$ decreases. For $g \geq 10$ ms, the average adaptation time is below 5 ms for the highest examined value of $\Gamma$ on all datasets. The average adaptation time for lower $\Gamma$ values is even smaller—below 1 ms. Moreover, in our implementation, the Buffer-Size Manager and the join operator run in separate threads; hence, the buffer-size adaptation time overlaps with the join processing time.

VII. RELATED WORK

MSWJ over Data Streams. Representative early work on processing MSWJs over data streams includes [4], [5], [20]. Viglas et al. [5] proposed the MJoin algorithm and showed
three approaches. We refer readers to our previous work [17] for a detailed discussion. Most existing work tries to either maximize the result quality or minimize the result latency. Work that attempts to balance these two requirements only considered controlling the tradeoff from the latency side, e.g., allowing a user to specify the desired buffer size for reordering input. In contrast, our work aims to control the tradeoff from the quality side.

**Load Shedding for Joins.** Our work is also closely related to load shedding in data stream processing, whose basic idea is to process a selected portion of input tuples when the available system resources (e.g., CPU, memory) cannot match the demand of the query. Existing work that focuses on join queries includes [3], [8], [19]. Result tuples produced under load shedding is only a subset of the true result tuples, and how to maximize the output rate under resource constraints is one of the key research topics. We can see that the effect of a dropped tuple during load shedding on the result quality is the same as that of an unsuccessfully handled out-of-order tuple during disorder handling. However, in load shedding, to determine which tuples to drop, we need to consider only the contribution of a tuple to the result quality based on its productivity; whereas in quality-driven disorder handling, to determine which out-of-order tuples could be handled unsuccessfully not only the productivity but also the delay of a tuple. Namely, one more dimension needs to be considered in quality-driven disorder handling.

**VIII. Conclusion**

In this paper, we proposed a buffer-based, adaptive, quality-driven disorder handling framework for processing MSWJs over out-of-order and unsynchronized data streams. The framework is generic and supports MSWJs with arbitrary join conditions. Moreover, we proposed a novel model-based approach for adapting the buffer size at runtime to minimize the result latency incurred by disorder handling, while honoring user-specified result-quality requirements. The proposed model directly captures the relationship between the buffer size and the recall of produced join results, thereby allowing to search for the optimal buffer size at each adaptation step. Experimental results showed the effectiveness of our approach. Compared to the state of the art, we can significantly reduce the applied buffer size for disorder handling, thus the incurred result latency, while still providing the desired result quality.

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