

# Adaptive Load Shedding for Windowed Stream Joins

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## ABSTRACT

We present an adaptive load shedding approach for windowed stream joins. In contrast to the conventional approach of dropping tuples from the input streams, we explore the concept of *selective processing* for load shedding, focusing on costly stream joins such as those over set-valued or weighted set-valued attributes. The main idea of our adaptive load shedding approach is two-fold. First, we allow stream tuples to be stored in the windows and shed excessive CPU load by performing the stream join operations, not on the entire set of tuples within the windows, but on a dynamically changing subset of tuples that are highly beneficial. Second, we support such dynamic selective processing through three forms of runtime *adaptations*: By *adaptation to input stream rates*, we perform partial processing based load shedding and dynamically determine the fraction of the windows to be processed by comparing the tuple consumption rate of join operation to the incoming stream rates. By *adaptation to time correlation between the streams*, we dynamically determine the number of basic windows to be used and prioritize the tuples for selective processing, encouraging CPU-limited execution of stream joins in high priority basic windows. By *adaptation to join directions*, we dynamically determine the most beneficial direction to perform stream joins in order to process more useful tuples under heavy load conditions and boost the utility or number of output tuples produced. Our load shedding framework not only enables us to integrate *utility-based* load shedding with *time correlation-based* load shedding, but more importantly, it also allows load shedding to be adaptive to various dynamic stream properties. Inverted indexes are used to further speed up the execution of stream joins based on set-valued attributes. Experiments are conducted to evaluate the effectiveness of our adaptive load shedding approach in terms of output rate and utility.

## 1. INTRODUCTION

With the ever increasing rate of digital information available from on-line sources and networked sensing devices [17], the management of bursty and unpredictable data streams has become a challenging problem. It requires solutions that will enable applications to effectively access and extract information from such data streams. A promising solution for this problem is to use declarative query processing engines specialized for handling data streams, such as data stream

management systems (DSMS), exemplified by Aurora [5], STREAM [1], and TelegraphCQ [7].

Joins are key operations in any type of query processing engine. Below we list some real-life application examples of stream joins. We return to these examples when we discuss assumptions about the characteristics of the joined streams in later sections.

- *Finding similar news items from two different sources:*  
Assuming that news items from two different sources (such as CNN, Reuters) are represented by weighted keywords (join attribute) in their respective streams, we can perform a windowed inner product join on them to find similar news items.
- *Finding correlated attacks from two different alert streams*  
Assuming that alerts from two different sources are represented by tuples in the form  $(source, target, \{attack\ descriptors\}, time)$  in their respective streams, we can perform a windowed overlap join on attack descriptors to find correlated attacks.
- *Finding correlation between phone calls and stock trading*  
Assuming that phone call streams are represented as  $\{\dots, (P_a, P_b, t_1), \dots\}$  where  $(P_a, P_b, t_1)$  means  $P_a$  calls  $P_b$  at time  $t_1$ , and stock trading streams are represented as  $\{\dots, (P_b, S_x, t_2), \dots\}$  where  $(P_b, S_x, t_2)$  means  $P_b$  trades  $S_x$  at time  $t_2$ ; we can perform a windowed equi-join on person attribute to find hints, such as:  $P_a$  hints  $S_x$  to  $P_b$  in the phone call.

As a result, joins on unbounded data streams have recently enjoyed strong interest in data stream management research [11, 14, 12]. This is mainly due to the fact that most of the traditional join algorithms are blocking operations. They need to perform a scan on one of the inputs to produce all result tuples that match with a given tuple from the other input. However, data streams are unbounded, thus blocking is not an option.

Several proposals have been put forth to address the problem of blocking joins, and they vary depending on the concrete applications at hand. One natural way of handling joins on infinite streams is to use sliding windows. In a windowed stream join, a tuple from one stream is joined with only the tuples currently available in the window of another stream. A sliding window can be defined as a *time-based* or *count-based* window. An example of a time-based window is “last 10 seconds’ tuples” and an example of a count-based window is “last 100 tuples.” Windows can be either user defined, in which case we have *fixed* windows, or system-defined and thus *flexible*, in which case the system uses the available memory to maximize the output size of the join. Another way of handling the problem of blocking joins is to use *punctuated streams* [24],

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in which punctuations that give hints about the rest of the stream are used to prevent blocking. The two-way stream joins with user defined time-based windows constitute one of the most common join types in the data stream management research to date [2, 11, 14].

In order to keep up with the incoming rates of streams, load shedding is usually needed in stream processing systems. Several factors may contribute to the demand for load shedding, including (a) bursty and unpredictable rates of the incoming streams; (b) large window sizes; and (c) costly join conditions. Data streams can be unpredictable in nature [15] and incoming stream rates tend to soar during peak times. A high stream rate requires more resources for performing a windowed join, due to both increased number of tuples received per unit time and the increased number of tuples within a fixed-sized time window. Similarly, large window sizes imply that more tuples are needed for processing a windowed join. Costly join conditions typically require more CPU time, such as join conditions defined on set-valued and weighted set-valued attributes.

A set-valued attribute naturally occurs when an attribute takes more than one value from a domain. For instance, an attribute *flagColor* can take the value  $\{white, red, green\}$ . Mostly used join conditions on set-valued attributes include subset ( $\subset$ ), equality ( $=$ ), superset ( $\supset$ ), and overlap ( $\theta_k$ ). Overlap join,  $\theta_k$ , finds the pair of tuples with set-valued attributes that share at least  $k$  items. For instance, an attribute *requiredSkills* can possibly take the values  $\{Java, Oracle, C++, XML\}$  and  $\{C, Java, BSc, Oracle\}$ , where the overlap of these two set values has 2 items  $\{Java, Oracle\}$ .

A weighted set value provides a stronger model to represent different objects. Any sparse point from a large vector space can be compactly represented as a set of weighted items. For instance, a document can be represented as a vector where dimensions represent words and coordinates represent weights of words (ex. assigned by tf-idf weighting [16]). This vector can be converted into a weighted set, where each item-weight pair in the set corresponds to a non-zero weighted word. Similarly a multimedia object can be represented as a feature vector and then converted into a weighted set. A typical join condition for weighted set-valued attributes can be inner product of their vector representations. An inner product join with threshold value  $d$ , tries to find pairs of attributes whose inner product is larger than or equal to  $d$ .

In this paper we propose an adaptive load shedding framework for costly windowed stream joins. The main idea is to reduce the amount of CPU load by judiciously performing joins on a selective subset of high-valued tuples from the windows and making the selection decision through dynamic adaptations to incoming stream rates, time-based correlation between streams, and join directions. Given that the output of a windowed stream join with load shedding is only a subset of the output of an off-line join, the goal of our load shedding, in the context of windowed stream joins, is to shed load in such a way that the *number* of output tuples produced or the *utility* gained by the produced tuples is maximized. Maximizing the utility of the output tuples produced is especially important when certain tuples are more valuable than others.

## Summary of Contributions

In the rest of paper we present an adaptive load shedding framework for windowed stream joins, aiming at maximizing both the output rate and the output utility of stream joins. We focus on costly stream joins such as those over set-valued

or weighted set-valued attributes. Our approach has several unique characteristics. First, instead of dropping tuples from the input streams as proposed in many existing approaches, our adaptive load shedding framework follows a selective processing methodology by keeping tuples within the windows, but processing only a subset of them, when they are more useful, based on time-based correlation between the streams. Second, our approach achieves load shedding by performing adaptation in three dimensions. Through rate adaptation, our stream join approach adapts to the incoming stream rates to shed load by adjusting the amount of selective processing. Through time correlation adaptation, the selective processing of stream joins adapts to the time-based correlation between the streams through the use of basic windows, prioritized based on the match probability density function learned from the analysis of streams. The learning is done by performing full processing instead of selective processing for a sampled part of the stream. Through join direction adaptation, our approach dynamically determines the most beneficial join direction by moving from symmetric-join to partial symmetric and partial asymmetric join as dictated by the load on the system. Third but not the least, our selective processing with three levels of adaptations enables a coherent integration with the utility-based load shedding, in order to maximize utility of the output tuples without resorting to dropping tuples in input streams. We employ inverted indexes, commonly used in set based join processing [18, 20], to our windowed stream joins to speed up the selective processing of joins. We include a set of experiments conducted to evaluate the effectiveness of our adaptive load shedding approach. Our experimental results show that the three levels of adaptations can effectively shed the load in the presence of bursty and unpredictable rates of the incoming streams, the large window sizes, and the costly join conditions, such as those on set-valued attributes.

## 2. ALTERNATIVE APPROACHES AND RELATED WORK

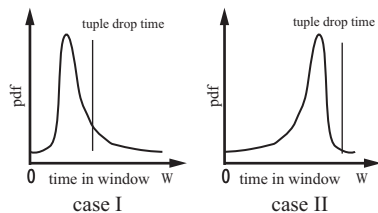
We can broadly divide the related work on load shedding in windowed stream joins into two categories, based on the metric being optimized.

The work in the first category aims at maximizing the utility of the output produced. Different tuples may have different importance values based on the application. For instance, in the news join example, certain type of news, e.g., security news, may be of higher value, and similarly in the stock trading example, phone calls from insiders may be of higher interest when compared to calls from regulars. In this case, an output from the join operator that contains highly-valued tuples is more preferable to a higher rate output generated from lesser-valued tuples. The work presented in [23] uses user-specified utility specifications to drop tuples from the input streams with low utility values. We refer to this type of load shedding as *utility based load shedding*, also referred to as *semantic load shedding* in the literature.

The work in the second category aims at maximizing the number of output tuples produced [9, 14, 22]. This can be achieved through rate reduction on the source streams, i.e., dropping tuples from the input streams, as suggested in [6, 14]. The work presented in [14] investigates algorithms for evaluating moving window joins over pairs of unbounded streams. Although the main focus of [14] is not on load shedding, scenarios where system resources are insufficient to keep up with the input streams are also considered.

There are several other works related with load shedding in DSMSs in general, including memory allocation among query operators [3] or inter-operator queues [19], load shedding for aggregation queries [4], and overload-sensitive management of archived streams [8].

In summary, most of the existing techniques used for shedding load are tuple dropping for CPU-limited scenarios and memory allocation among windows for memory-limited scenarios. However, dropping tuples from the input streams without paying attention to the selectivity of such tuples may result in a suboptimal solution. Based on this observation, heuristics that take into account selectivity of the tuples are proposed in [9].



**Figure 1: Examples of match probability density functions**

A different approach, called *age-based* load shedding, is proposed recently in [22] for performing memory-limited stream joins. This work is based on the observation that there exists a time-based correlation between the streams. Concretely, the probability of having a match between a tuple just received from one stream and a tuple residing in the window of the opposite stream, may change based on the difference between the timestamps of the tuples (assuming timestamps are assigned based on the arrival times of the tuples at the query engine). Under this observation, memory is conserved by keeping a tuple in the window since its reception until the average rate of output tuples generated using this tuple reaches its maximum value. For instance, in Figure 1 case I, the tuples can be kept in the window until they reach the vertical line marked. This effectively cuts down the memory needed to store the tuples within the window and yet produces an output close to the actual output without window reduction.

Obviously, knowing the distribution of the incoming streams has its peak at the beginning of the window, the age-based window reduction can be effective for shedding memory load. A natural question to ask is: “Can the age-based window reduction approach of [22] be used to shed CPU load?” This is a valid question, because reducing the window size also decreases the number of comparisons that have to be made in order to evaluate the join. However, as illustrated in Figure 1 case II, this technique cannot directly extend to the CPU-limited case where the memory is not the constraint. When the distribution does not have its peak close to the beginning of the window, the window reduction approach has to keep tuples until they are close to the end of the window. As a result, tuples that are close to the beginning of the window and thus are not contributing much to the output will be processed until the peak is reached close to the end of the window. This observation points out two important facts. First, time-based correlation between the windowed streams can play an important role in load shedding. Second, the window reduction technique that is effective for utilizing time-based correlation to shed memory load is not suitable for CPU load shedding, especially when the distribution of the incoming streams is unknown or unpredictable.

With the above analysis in mind, we propose an adaptive load shedding framework that is capable of performing selective processing of tuples in the stream windows by dynamic

adaptation to input stream rates, time-based correlations between the streams, and profitability of different join directions. To our knowledge, our load shedding approach is the only one that can handle arbitrary time correlations and at the same time can support maximization of output utility.

### 3. OVERVIEW

Unlike the conventional load shedding approach of dropping tuples from the input streams, our adaptive load shedding framework encourages stream tuples to be kept in the windows and sheds the CPU load by performing the stream joins on a dynamically changing subset of tuples that are highly beneficial, instead of on the entire set of tuples stored within the windows. This allows us to exploit the characteristics of stream applications that exhibit time based correlation between the streams. Concretely, we assume that there exists a non-flat distribution of probability of match between a newly-received tuple and the other tuples in the opposite window, depending on the difference between the timestamps of the tuples. There are several reasons behind this assumption. First, variable delays can exist between the streams as a result of differences between the communication overhead of receiving tuples from different sources [21]. Second and more importantly, there may exist variable delays between related events from different sources. For instance, in the news join example, different news agencies are expected to have different reaction times due to differences in their news collection and publishing processes. In the stock trading example, there will be a time delay between the phone call containing the hint and the action of buying the hinted stock. In the correlated attacks example, different parts of the network may have been attacked at different times. Note that, the effects of time correlation on the data stream joins are to some extent analogous to the effects of the time of data creation in data warehouses, which are exploited by join algorithms such as Drag-Join [13].

Although our load shedding framework is based on the assumption that the memory resource is sufficient, we want to point out two important observations. First, with increasing input stream rates and larger stream window sizes, it is quite common that the processing resources (CPU) become limited before memory does. Second, it is interesting to note that, even under limited memory, our adaptive load shedding approach can be used to effectively shed the excessive CPU load after window reduction is performed for handling the memory constraints.

#### 3.1 Technical Highlights

Our load shedding approach is best understood through its two core mechanisms, each answers a fundamental question on adaptive load shedding without tuple dropping. The first mechanism is called *partial processing* and it answers the question of “*how much we can process*” given a window of stream tuples. The factors to be considered in answering this question include the performance of the stream join operation under current system load and the current incoming stream rates. In particular, partial processing dynamically adjusts the amount of load shedding to be performed through rate adaptation. The second mechanism is called *selective processing* and it answers the question of “*what should we process*” given the constraint on the amount of processing, defined at the partial processing phase. The factors that influence the answer to this question include the characteristics of stream

window segments, the profitability of join directions, and the utility of different stream tuples. Selective processing extends partial processing to intelligently select the tuples to be used during join processing under heavy system load, with the goal of maximizing the output rate or the output utility of the stream join.

Notation	Meaning
$t$	tuple
$T(t)$	timestamp of the tuple $t$
$S_i$	input stream $i$
$W_i$	window over $S_i$
$w_i$	window size of $W_i$ in seconds
$\lambda_i$	rate of $S_i$ in tuples per second
$B_{i,j}$	basic window $j$ in $W_i$
$b$	basic window size in seconds
$n_i$	number of basic windows in $W_i$
$r$	fraction parameter
$\delta_r$	fraction boost factor
$r_i$	fraction parameter for $W_i$
$r_{i,z}$	fraction parameter for $W_i$ for a tuple of type $z$
$f_i(t)$	match probability density function for $W_i$
$p_{i,j}$	probability of match for $B_{i,j}$
$o_{i,j}$	expected output from comparing a tuple $t$ with a tuple in $B_{i,j}$
$s_i^j$	$k$ , where $o_{i,k}$ is the $j$ th item in the sorted list $\{o_{i,l}   l \in [1..n_i]\}$
$u_{i,z}$	expected utility from comparing a tuple $t$ of type $z$ with a tuple in $W_i$
$Z$	tuple type domain
$Z(t)$	type of a tuple
$V(z)$	utility of a tuple of type $z$
$\omega_{i,z}$	frequency of a tuple of type $z$ in $S_i$
$T_r$	rate adaptation period
$T_c$	time correlation adaptation period
$\gamma$	sampling probability

Table 1: Notations used throughout the paper

Before describing the details of partial processing and selective processing, we first briefly review the basic concepts involved in processing windowed stream joins, and establish the notations that will be used throughout the paper.

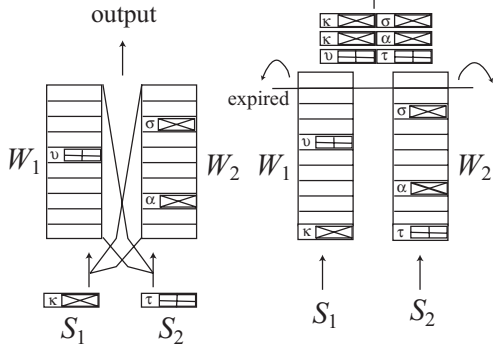


Figure 2: Stream Join Example

### 3.2 Basic Concepts and Notations

A two-way windowed stream join operation takes two input streams denoted as  $S_1$  and  $S_2$ , performs the stream join and generates the output. For notational convenience, we denote the opposite stream of stream  $i$  ( $i = 1, 2$ ) as stream  $\bar{i}$ . The sliding window defined over stream  $S_i$  is denoted as  $W_i$ , and has size  $w_i$  in terms of seconds. We denote a tuple as  $t$  and its arrival timestamp as  $T(t)$ . Other notations will be introduced in the rest of the paper as needed. Table 1 summarizes the notations used throughout the paper.

A windowed stream join is performed by fetching tuples from the input streams and processing them against tuples in the opposite window. Figure 2 illustrates the process of windowed stream joins. For a newly fetched tuple  $t$  from stream  $S_i$ , the join is performed in the following three steps. First, tuple  $t$  is inserted into the beginning of window  $W_i$ . Second, tuples at the end of window  $W_i$  are checked in order and removed if they have expired. A tuple  $t_o$  expires from window  $W_i$  iff  $T - T(t_o) > w_i$ , where  $T$  represents the current time. The expiration check stops when an unexpired tuple is encountered. The tuples in window  $W_i$  are sorted in the order of their arrival timestamps by default and the window is managed as a doubly linked list for efficiently performing insertion and expiration operations. In the third and last step, tuple  $t$  is processed against tuples in the window  $W_{\bar{i}}$ , and matching tuples are generated as output.

Figure 3 summarizes the join processing steps. To handle joins defined on set or weighted set valued attributes, the following additional details are attached to the processing steps, assuming a tuple is a set of items (possibly with assigned weights). First, the items in tuple  $t$  are sorted as it is fetched from  $S_i$ . The tuples in  $W_{\bar{i}}$  are expected to be sorted, since they have gone through the

```

JOIN PROCESSING()
for i = 1 to 2
  if no tuple in  $S_i$ 
    continue
   $t \leftarrow$  fetch tuple from  $S_i$ 
  Insert  $t$  in front of  $W_i$ 
  repeat
     $t_o \leftarrow$  last tuple in  $W_i$ 
    if  $T - T(t_o) > w_i$ 
      Remove  $t_o$  from  $W_i$ 
  until  $T - T(t_o) \leq w_i$ 
  Sort items in  $t$ 
  foreach  $t_a \in W_{\bar{i}}$ 
    Merge compare  $t, t_a$ 

```

Figure 3: Join Processing

same step when they were fetched from  $S_{\bar{i}}$ . Then, for each tuple  $t_a$  in  $W_{\bar{i}}$ ,  $t$  and  $t_a$  are compared by performing a simple merge of their sorted items. Equality, subset, superset, overlap and inner product joins all can be processed in a similar manner. For indexed joins, an inverted index is used to efficiently perform the join without going through all the tuples in  $W_{\bar{i}}$ . We discuss the details of indexed join in Section 4.2.

## 4. PARTIAL PROCESSING - HOW MUCH WE CAN PROCESS?

The first step in our approach to shedding CPU load without dropping tuples is to determine how much we can process given the windows of stream tuples that participate in the join. We call this step the partial processing based load shedding. For instance, consider a scenario in which the limitation in processing power requires to drop half of the tuples, i.e. decreasing the input rate of the streams by half. A partial processing approach is to allow every tuple to enter into the windows, but to decrease the cost of join processing by comparing a newly-fetched tuple with only a fraction of the window defined on the opposite stream. Partial processing, by itself, does not significantly increase the number of output tuples produced by the join operator, when compared to tuple dropping or window reduction approaches. However, as we will describe later in the paper, it forms a basis to perform selective processing, which exploits the time-based correlation between the streams, and makes it possible to accommodate utility-based load shedding, in order to maximize the output rate or the utility of the output tuples produced. Two important factors are considered in determining the amount of partial processing: (1) the current incoming stream rates, and (2) the performance of the stream join operation under cur-

### Algorithm 1: Rate Adaptation

```

RATEADAPT()
(1) Initially:  $r \leftarrow 1$ 
(2) every  $T_r$  seconds
(3)    $\alpha_1 \leftarrow \#$  of tuples fetched from  $S_1$  since last adapt.
(4)    $\alpha_2 \leftarrow \#$  of tuples fetched from  $S_2$  since last adapt.
(5)    $\lambda_1 \leftarrow$  average rate of  $S_1$  since last adaptation
(6)    $\lambda_2 \leftarrow$  average rate of  $S_2$  since last adaptation
(7)    $\beta \leftarrow \frac{\alpha_1 + \alpha_2}{(\lambda_1 + \lambda_2) * T_r}$ 
(8)   if  $\beta < 1$  then  $r \leftarrow \beta * r$ 
(9)   else  $r \leftarrow \min(1, \delta_r * r)$ 

```

rent system load. Partial processing employs rate adaptation to adjust the amount of processing performed dynamically. The performance of the stream join under the current system load is a critical factor and it is influenced by the concrete join algorithm and optimizations used for performing join operations.

In the rest of this section, we first describe rate adaptation, then discuss the details of utilizing inverted indexes for efficient join processing. Finally we describe how to employ rate adaptation in conjunction with indexed join processing.

## 4.1 Rate Adaptation

The partial processing-based load shedding is performed by adapting to the rates of the input streams. This is done by observing the tuple consumption rate of the join operation and comparing it to the input rates of the streams to determine the fraction of the windows to be processed. This adaptation is performed periodically, at every  $T_r$  seconds.  $T_r$  is called the *adaptation period*. We denote the fraction parameter as  $r$ , which defines the ratio of the windows to be processed. In other words, the setting of  $r$  answers the question of *how much* load we should shed.

Algorithm 1 gives a sketch of the rate adaptation process. Initially, the fraction parameter  $r$  is set to 1. Every  $T_r$  seconds, the average rates of the input streams  $S_1$  and  $S_2$  are determined as  $\lambda_1$  and  $\lambda_2$ . Similarly, the number of tuples fetched from streams  $S_1$  and  $S_2$  since the last adaptation step are determined as  $\alpha_1$  and  $\alpha_2$ . Tuples from the input streams may not be fetched at the rate they arrive due to an inappropriate initial value of the parameter  $r$  or due to a change in the stream rates since the last adaptation step. As a result,  $\beta = \frac{\alpha_1 + \alpha_2}{(\lambda_1 + \lambda_2) * T_r}$  determines the percentage of the input tuples fetched by the join algorithm. Based on the value of  $\beta$ , the fraction parameter  $r$  is readjusted at the end of each adaptation step. If  $\beta$  is smaller than 1,  $r$  is multiplied by  $\beta$ , with the assumption that comparing a tuple with the other tuples in the opposite window has the dominating cost in join processing. Otherwise, the join is able to process all the incoming tuples with the current value of  $r$ . In this case, the  $r$  value is set to  $\min(1, \delta_r * r)$ , where  $\delta_r$  is called the *fraction boost factor*. This is aimed at increasing the fraction of the windows processed, optimistically assuming that additional processing power is available. If not, the parameter  $r$  will be decreased during the next adaptation step. Higher values of the fraction boost factor result in being more aggressive at increasing the parameter  $r$ . The adaptation period  $T_r$  should be small enough to adapt to the bursty nature of the streams, but large enough not to cause overhead and undermine the join processing.

## 4.2 Indexed Join and Partial Processing

Stream indexing [10, 25] can be used to cope up with the high processing cost of the join operation, reducing the

amount of load shedding performed. However, there are two important points to be resolved before indexing can be employed together with partial processing and thus with other algorithms we introduce in the following sections. The first issue is that, in a streaming scenario the index has to be maintained dynamically (through insertions and removals) as the tuples enter and leave the window. This means that the assumption made in Section 4.1 about finding matching tuples within a window (index search cost) being the dominant cost in the join processing, no more holds. Second, the index does not naturally allow to process only a certain portion of the window. We resolve these issues in the context of inverted indexes, that are predominantly used for joins based on set or weighted set-valued attributes. Here, we first give a brief overview of inverted indexes and then describe the modifications required to use them in conjunction with our load shedding algorithms.

### 4.2.1 Inverted Indexes

An inverted index consists of a collection of sorted identifier lists. In order to insert a set into the index, for each item in the set, the unique identifier of the set is inserted into the identifier list associated with that particular item. Similar to insertion, removal of a set from the index requires to find the identifier lists associated with the items in the set. The removal is performed by removing the identifier of the set from these identifier lists. In our context, the inverted index is maintained as an in-memory data structure. The collection of identifier lists are managed in a hashtable. The hashtable is used to efficiently find the identifier list associated with an item. The identifier lists are internally organized as sorted (based on unique set identifiers) balanced binary trees to facilitate both fast insertion and removal. The set identifiers are in fact pointers to the tuples they represent.

Query processing on an inverted index follows a multi-way merging process, which is usually accelerated through the use of a heap. Same type of processing is used for all different types of queries we have mentioned so far. Specifically, given a query set, the identifier lists corresponding to items in the query set are retrieved using the hashtable. These sorted identifier lists are then merged. This is done by inserting the frontiers of the lists into a min heap and iteratively removing the topmost set identifier from the heap and replacing it with the next set identifier (new frontier) in its list. During this process, the identifier of an indexed set, sharing  $k$  items with the query set, will be picked from the heap  $k$  consecutive times, making it possible to process relatively complex overlap and inner product<sup>1</sup> queries efficiently [18].

### 4.2.2 Time Ordered Identifier Lists

Although the usage of inverted indexes speeds up the processing of joins based on set-valued attributes, it also introduces significant insertion and deletion costs. This problem can be alleviated by exploiting the timestamps of the tuples that are being indexed and the fact that these tuples are received in timestamp order from the input streams. In particular, instead of maintaining identifier lists as balanced trees sorted on identifiers, we can maintain them as linked lists sorted on timestamps of the tuples (sets). This does not effect the merging phase of the indexed search, since a timestamp uniquely identifies a tuple in a stream unless different tuples

<sup>1</sup>For weighted sets, the weights should also be stored within the identifier lists, in order to answer inner product queries.

with equal timestamps are allowed. In order to handle the latter, the identifier lists can be sorted based on (timestamp, identifier) pairs. This requires very small reordering, as the event of receiving different tuples with equal timestamps is expected to happen very infrequently, if it happens at all. Using timestamp ordered identifier lists has the following three advantages:

1. It allows to insert a set identifier into an identifier list in constant time, as opposed to logarithmic time with identifier sorted lists.
2. It facilitates piggybacking of removal operations on insertion and search operations, by checking for expired tuples at the end of identifier lists at insertion and search time. Thus, the removal operation is performed in amortized constant time as opposed to logarithmic time with identifier sorted lists.
3. Timestamp sorted identifier lists make it possible to end the merging process, used for search operations, at a specified time within the window, thus enabling time based partial processing.

This concludes our discussion of indexed join details.

## 5. SELECTIVE PROCESSING - WHAT SHOULD WE PROCESS?

Selective processing extends partial processing to intelligently select the tuples to be used during join processing under heavy system load. Given the constraint on the amount of processing defined at the partial processing phase, the selective processing aims at maximizing the output rate or the output utility of the stream joins. Three important factors are used to determine what we should select for join processing: (1) the characteristics of stream window segments, (2) the profitability of join directions, and (3) the utility of different stream tuples. We first describe time correlation adaptation and join direction adaptation, which form the core of our selective processing approach. Then we discuss utility-based load shedding. The main ideas behind time correlation adaptation and join direction adaptation are to prioritize segments of the windows in order to process parts that will yield higher output (time correlation adaptation) and to start load shedding from one of the windows if one direction of the join is producing more output than the other (join direction adaptation).

### 5.1 Time Correlation Adaptation

For the purpose of time correlation adaptation, we divide the windows of the join into *basic windows*. Concretely, window  $W_i$  is divided into  $n_i$  basic windows of size  $b$  seconds each, where  $n_i = 1 + \lceil w_i/b \rceil$ .  $B_{i,j}$  denotes the  $j$ th basic window in  $W_i$ ,  $j \in [1..n_i]$ . Tuples do not move from one basic window to another. As a result, tuples leave the join operator one basic window at a time and the basic windows slide discretely  $b$  seconds at a time. The newly fetched tuples are inserted into the first basic window. When the first basic window is full, meaning that the newly fetched tuple has a timestamp that is at least  $b$  seconds larger than the oldest tuple in the first basic window, the last basic window is emptied and all the basic windows are shifted, last basic window becoming the first. The newly fetched tuples can now flow into the new first basic window, which is empty. The basic windows are managed in a circular buffer, so that the shift of windows is a

### Algorithm 2: Time Correlation Adaptation

```

TIMECORRELATIONADAPT()
(1) every  $T_c$  seconds
(2) for  $i = 1$  to 2
(3)   sort in desc. order  $\{\hat{o}_{i,j} | j \in [1..n_i]\}$  into array  $O$ 
(4)   for  $j = 1$  to  $n_i$ 
(5)      $o_{i,j} \leftarrow \frac{\hat{o}_{i,j}}{\gamma * r * b * \lambda_2 * \lambda_1 * T_c}$ 
(6)      $s_i^j \leftarrow k$ , where  $O[j] = \hat{o}_{i,k}$ 
(7)   for  $j = 1$  to  $n_i$ 
(8)      $\hat{o}_{i,j} \leftarrow 0$ 

```

### Algorithm 3: Tuple Processing and Time Correlation

```

PROCESSTUPLE()
(1) when processing tuple  $t$  against window  $W_i$ 
(2)   if  $rand < r * \gamma$ 
(3)     process  $t$  against all tuples in  $B_{i,j}, \forall j \in [1..n_i]$ 
(4)     foreach match in  $B_{i,j}, \forall j \in [1..n_i]$ 
(5)        $\hat{o}_{i,j} \leftarrow \hat{o}_{i,j} + 1$ 
(6)   else
(7)      $a \leftarrow r * |W_i|$ 
(8)     for  $j = 1$  to  $n_i$ 
(9)        $a \leftarrow a - |B_{i,s_i^j}|$ 
(10)    if  $a > 0$ 
(11)      process  $t$  against all tuples in  $B_{i,s_i^j}$ 
(12)    else
(13)       $r_e \leftarrow 1 + \frac{a}{|B_{i,s_i^j}|}$ 
(14)    process  $t$  against  $r_e$  fraction of tuples in  $B_{i,s_i^j}$ 
(15)    break

```

constant time operation. The basic windows themselves can be organized as either linked lists (if no indexing is used) or as inverted indexes (if indexing is used).

Time correlation adaptation is periodically performed at every  $T_c$  seconds.  $T_c$  is called the *time correlation adaptation period*. During the time between two consecutive adaptation steps, the join operation performs two types of processing. For a newly fetched tuple, it either performs *selective processing* or *full processing*. Selective processing is carried out by looking for matches with tuples in high priority basic windows of the opposite window, where the number of basic windows used depends on the amount of load shedding to be performed. Full processing is done by comparing the newly fetched tuple against all the tuples from the opposite window. The aim of full processing is to collect statistics about the usefulness of the basic windows for the join operation.

The details of the adaptation step and full processing are given in Algorithm 2 and in lines 1-5 of Algorithm 3. Full processing is only done for a sampled subset of the stream, based on a parameter called *sampling probability*, denoted as  $\gamma$ . A newly fetched tuple goes through selective processing with probability  $1 - r * \gamma$ . In other words, it goes through full processing with probability  $r * \gamma$ . The fraction parameter  $r$  is used to scale the sampling probability, so that the full processing does not consume all processing resources when the load on the system is high. The goal of full processing is to calculate for each basic window  $B_{i,j}$ , the expected number of output tuples produced from comparing a newly fetched tuple  $t$  with a tuple in  $B_{i,j}$ , denoted as  $o_{i,j}$ . These values are used later during the adaptation step to prioritize windows. In particular,  $o_{i,j}$  values are used to calculate  $s_i^j$  values. We have  $s_i^j = k$ , where  $o_{i,k}$  is the  $j$ th item in the sorted list  $\{o_{i,l} | l \in [1..n_i]\}$ . This means that  $B_{i,s_i^1}$  is the highest priority basic window in  $W_i$ ,  $B_{i,s_i^2}$  is the next, and so on.

Lines 7-14 in Algorithm 3 give a sketch of selective processing. During selective processing,  $s_i^j$  values are used to



guide the load shedding. Concretely, in order to process a newly fetched tuple  $t$  against window  $W_i$ , first the number of tuples from window  $W_i$ , that are going to be considered for processing, is determined by calculating  $r * |W_i|$ , where  $|W_i|$  denotes the number of tuples in the window. The fraction parameter  $r$  is determined by rate adaptation as described in Section 4.1. Then, tuple  $t$  is processed against basic windows, starting from the highest priority one, i.e.  $B_{i,s_i^1}$ , going in decreasing order of priority. A basic window  $B_{i,s_i^j}$  is searched for matches completely, if adding  $|B_{i,s_i^j}|$  number of tuples to the number of tuples used so far from window  $W_i$  to process tuple  $t$  does not exceeds  $r * |W_i|$ . Otherwise an appropriate fraction of the basic window is used and the processing is completed for tuple  $t$ .

### 5.1.1 Impact of Basic Window Size

The setting of basic window size parameter  $b$  involves trade-offs. Smaller values are better to capture the peak of the match probability distribution, while they also introduce overhead in processing. For instance, recalling Section 4.2.1, in an indexed join operation, the identifier lists have to be looked up for each basic window. Although the lists themselves are shorter and the total merging cost does not increase with smaller basic windows, the cost of looking up the identifier lists from the hashtables increases with increasing number of basic windows,  $n_i$ .

Here we analyze how well the match probability distribution, which is dependent on the time correlation between the streams, is utilized for a given value of the basic window size parameter  $b$ , under a given load condition. We use  $r'$  to denote the fraction of tuples in join windows that can be used for processing tuples. Thus,  $r'$  is used to model the current load of the system. We assume that  $r'$  can go over 1, in which case abundant processing power is available.

We use  $f_i(t)$  to denote the match probability distribution function for window  $W_i$ . Note that, due to discrete movement of basic windows, a basic window covers a time varying area under the match probability distribution function. This area, denoted as  $p_{i,j}$  for basic window  $B_{i,j}$ , can be calculated by observing that the basic window  $B_{i,j}$  covers the area over the interval  $[max(0, x * b + (j - 2) * b), min(w_i, x * b + (j - 1) * b)]$  on the time axis ( $[0, w_i]$ ), when only  $x \in [0, 1]$  fraction of the first basic window is full. Then, we have:

$$p_{i,j} = \int_{x=0}^1 \int_{t=max(0, x*b+(j-2)*b)}^{min(w_i, x*b+(j-1)*b)} f_i(t) dt dx$$

For the following discussion, we overload the notation  $s_i^j$ , such that  $s_i^j = k$ , where  $p_{i,k}$  is the  $j$ th item in the sorted list  $\{p_{i,l} | l \in [1..n_i]\}$ . The number of basic windows whose tuples are all considered for processing is denoted as  $c_e$ . The fraction of tuples in the last basic window used, that are considered for processing, is denoted as  $c_p$ .  $c_p$  is zero if the last used basic window is completely processed. We have:

$$c_e = \min(n_i, \lfloor r' * w_i / b \rfloor)$$

$$c_p = \begin{cases} \frac{r' * w_i - c_e * b}{b} & c_e < n_i \\ 0 & otherwise \end{cases}$$

Then the area under  $f_i$  that represents the portion of window  $W_i$  processed, denoted as  $p_u$ , can be calculated as:

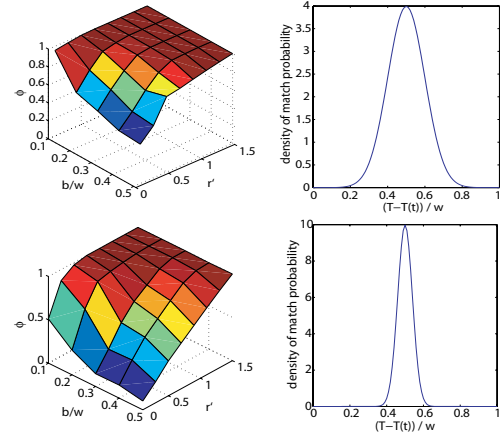
$$p_u \approx c_p * p_{s_i^{c_e+1}} + \sum_{j=1}^{c_e} p_{i,s_i^j}$$

Let us define  $g(f_i, a)$  as the maximum area under the function  $f_i$  with a total extent of  $a$  on the time axis. Then we can calculate the optimality of  $p_u$ , denoted as  $\phi$ , as follows:

$$\phi = \frac{p_u}{g(f_i, w_i * \min(1, r'))}$$

When  $\phi = 1$ , the join processing is optimal with respect to output rate (ignoring the overhead of small basic windows). Otherwise, the expected output rate is  $\phi$  times the optimal value, under current load conditions ( $r'$ ) and basic window size setting ( $b$ ). Figure 4 plots  $\phi$  (on  $z$ -axis) as a function of  $b/w_i$  (on  $x$ -axis) and  $r'$  (on  $y$ -axis) for two different match probability distributions, the bottom one being more skewed. We make the following three observations from the figure:

- Decreasing availability of computational resources negatively influences the optimality of the join for a fixed basic window size.
- The increasing skewness in the match probability distribution decreases the optimality of the join for a fixed basic window size.
- Smaller basic windows sizes provide better join optimality, when the available computational resources are low or the match probability distribution is skewed.



**Figure 4: Optimality of the join for different loads and basic window sizes under two different match probability distribution functions**

As a result, small basic window sizes are favorable for skewed probability match distributions and heavy load conditions. We report our experimental study on the effect of overhead, stemming from managing large number of basic windows, on the output rate of the join operation in Section 6.

## 5.2 Join Direction Adaptation

Due to time based correlation between the streams, a newly fetched tuple from stream  $S_1$  may match with a tuple from stream  $S_2$  that has already made its way into the middle portions of window  $W_2$ . This means that, most of the time, a newly fetched tuple from stream  $S_2$  has to stay within the window  $W_2$  for some time, before it can be matched with a tuple from stream  $S_1$ . This implies that, one direction of the join processing may be of lesser value, in terms of the number of output tuples produced, than the other direction. For instance, in the running example, processing a newly fetched tuple  $t$  from stream  $S_2$  against window  $W_1$  will produce smaller number of output tuples when compared to the other way

around, as the tuples to match  $t$  has not yet arrived at window  $W_1$ . In this case, symmetry of the join operation can be broken during load shedding, in order to achieve a higher output rate. This can be achieved by decreasing the fraction of tuples processed from window  $W_2$  first, and from  $W_1$  later (if needed). We call this *join direction adaptation*.

Join direction adaptation is performed immediately after rate adaptation. Specifically, two different fraction parameters are defined, denoted as  $r_i$  for window  $W_i$ ,  $i \in \{1, 2\}$ . During join processing,  $r_i$  fraction of the tuples in window  $W_i$  are considered, making it possible to adjust join direction by changing  $r_1$  and  $r_2$ . This requires to replace  $r$  with  $r_i$  in line 7 of Algorithm 3 and line 5 of Algorithm 2.

The constraint in setting of  $r_i$  values is that, the number of tuple comparisons performed per time unit should stay the same when compared to the case where there is a single  $r$  value as computed by Algorithm 1. The number of tuple comparisons performed per time unit is given by  $\sum_{i=1}^2 (r_i * \lambda_i * (\lambda_i * w_i))$ , since the number of tuples in window  $W_i$  is  $\lambda_i * w_i$ . Thus, we should have  $\sum_{i=1}^2 (r * \lambda_i * (\lambda_i * w_i)) = \sum_{i=1}^2 (r_i * \lambda_i * (\lambda_i * w_i))$ , i.e.:

$$r * (w_1 + w_2) = r_1 * w_1 + r_2 * w_2$$

The valuable direction of the join can be determined by comparing the expected number of output tuples produced from comparing a newly fetched tuple with a tuple in  $W_i$ , denoted as  $o_i$ , for  $i = 1$  and  $2$ . This can be computed as  $o_i = \frac{1}{n_i} * \sum_{j=1}^{n_i} o_{i,j}$ . Assuming  $o_1 > o_2$ , without loss of generality, we can set  $r_1 = \min(1, r * \frac{w_1 + w_2}{w_1})$ . This maximizes  $r_1$ , while respecting the above constraint. The generic procedure to set  $r_1$  and  $r_2$  is given in Algorithm 4.

Join direction adaptation, as it is described in this section, assumes that any portion of one of the windows is more valuable than all portions of the other window. This may not be the case for applications where both match probability distribution functions,  $f_1(t)$  and  $f_2(t)$ , are non-flat. For instance, in a traffic application scenario, a two way traffic flow between two points implies both directions of the join are valuable. We introduce a more advanced join direction adaptation algorithm, that can handle such cases, in the next subsection as part of utility-based load shedding.

### 5.3 Utility-based Load Shedding

So far, we have targeted our load shedding algorithms toward maximizing the number of tuples produced by the join operation, a commonly used metric in the literature [9, 22]. Utility-based load shedding, also called semantic load shedding [23], is another metric employed for guiding load shedding. It has the benefit of being able to distinguish high utility output from output containing large number of tuples. In the context of join operations, utility-based load shedding promotes output that results from matching tuples of higher importance/utility. In this section, we describe how

**Algorithm 4:** Join Direction Adaptation

```

JOINDIRECTIONADAPT()
(1) Initially:  $r_1 \leftarrow 1, r_2 \leftarrow 1$ 
(2) upon completion of RATEADAPT() call
(3)  $o_1 \leftarrow \frac{1}{n_1} * \sum_{j=1}^{n_1} o_{1,j}$ 
(4)  $o_2 \leftarrow \frac{1}{n_2} * \sum_{j=1}^{n_2} o_{2,j}$ 
(5) if  $o_1 \geq o_2$  then  $r_1 \leftarrow \min(1, r * \frac{w_1 + w_2}{w_1})$ 
(6) else  $r_1 \leftarrow \max(0, r * \frac{w_1 + w_2}{w_1} - \frac{w_2}{w_1})$ 
(7)  $r_2 \leftarrow r * \frac{w_1 + w_2}{w_1} - r_1 * \frac{w_1}{w_2}$ 

```

utility-based load shedding is integrated into the mechanism described until now.

We assume that each tuple has an associated importance level, defined by the *type* of the tuple, and specified by the *utility* value attached to that type. We denote the tuple type domain as  $\mathcal{Z}$ , type of a tuple  $t$  as  $Z(t)$ , and utility of a tuple  $t$ , where  $Z(t) = z \in \mathcal{Z}$ , as  $\mathcal{V}(z)$ . Type domains and their associated utility values can be set based on application needs. In the rest of the paper, the utility value of an output tuple of the the join operation that is obtained by matching tuples  $t_a$  and  $t_b$ , is assumed to contribute a utility value of  $\max(\mathcal{V}(Z(t_a)), \mathcal{V}(Z(t_b)))$  to the output. Our approach can also accommodate other functions, like average ( $0.5 * (\mathcal{V}(Z(t_a)) + \mathcal{V}(Z(t_b)))$ ). We denote the frequency of appearance of a tuple of type  $z$  in stream  $S_i$  as  $\omega_{i,z}$ , where  $\sum_{z \in \mathcal{Z}} \omega_{i,z} = 1$ .

The main idea behind utility-based load shedding is to use a different fraction parameter for each different type of tuple fetched from a different stream, denoted as  $r_{i,z}$ , where  $z \in \mathcal{Z}$  and  $i \in \{1, 2\}$ . The motivation behind this is to do less load shedding for tuples that provide higher output utility. The extra work done for such tuples is compensated by doing more load shedding for tuples that provide lower output utility. The expected output utility obtained from comparing a tuple  $t$  of type  $z$  with a tuple in window  $W_i$  is denoted as  $u_{i,z}$ , and is used to determine  $r_{i,z}$  values.

In order to formalize this problem, we extend some of the notation from Section 5.1.1. The number of basic windows from  $W_i$  whose tuples are all considered for processing against a tuple of type  $z$ , is denoted as  $c_e(i, z)$ . The fraction of tuples in the last basic window used from  $W_i$ , that are considered for processing, is denoted as  $c_p(i, z)$ .  $c_p(i, z)$  is zero if the last used basic window is completely processed. Thus, we have:

$$\begin{aligned} c_e(i, z) &= \lfloor n_i * r_{i,z} \rfloor \\ c_p(i, z) &= n_i * r_{i,z} - c_e(i, z) \end{aligned}$$

Then, the area under  $f_i$  that represents the portion of window  $W_i$  processed for a tuple of type  $z$ , denoted as  $p_u(i, z)$ , can be calculated as follows:

$$p(i, z) \approx c_p(i, z) * p_{i, s_i^{c_e(i,z)+1}} + \sum_{j=1}^{c_e(i,z)} p_{i, s_i^j}$$

With these definitions, the maximization of the output utility can be defined formally as

$$\max \sum_{i=1}^2 \left( \lambda_i * (\lambda_i * w_i) * \sum_{z \in \mathcal{Z}} (\omega_{i,z} * u_{i,z} * p(i, z)) \right)$$

subject to the processing constraint:

$$r * (w_2 + w_1) = \sum_{i=1}^2 \left( w_i * \sum_{z \in \mathcal{Z}} (\omega_{i,z} * r_{i,z}) \right)$$

The  $r$  value used here is computed by Algorithm 1, as part of rate adaptation. Although the formulation is complex, this is indeed a fractional knapsack problem and has a greedy optimal solution. This problem can be reformulated<sup>2</sup> as follows: Consider  $\mathcal{I}_{i,j,z}$  as an item that represents processing of a tuple of type  $z$  against basic window  $B_{i,j}$ . Item  $\mathcal{I}_{i,j,z}$  has a volume of  $\lambda_1 * \lambda_2 * \omega_{i,z} * b$  units (which is the number of comparisons made per time unit to process incoming tuples of type  $z$  against tuples in  $B_{i,j}$ ) and a value of

<sup>2</sup>assuming that some buffering is performed outside the join



**Algorithm 5:** Join Direction Adapt, Utility-based Shedding  
VJOINADAPT()

```

(1) upon completion of RATEADAPT() call
(2)   heap:  $H$ 
(3)   for  $i = 1$  to 2
(4)     foreach  $z \in \mathcal{Z}$ 
(5)        $r_{i,z} \leftarrow 0$ 
(6)        $v_{i,s_i^z} \leftarrow u_{i,z} * n_i * o_{i,s_i^z} / \sum_{k=1}^{n_i} o_{i,k}$ 
(7)   Initialize  $H$  with  $\{v_{i,s_i^z} | i \in [1..2], z \in \mathcal{Z}\}$ 
(8)    $a \leftarrow \lambda_1 * \lambda_2 * r * (w_1 + w_2)$ 
(9)   while  $H$  is not empty
(10)    use  $i, j, z$  s.t.  $v_{i,j,z} =$  topmost item in  $H$ 
(11)    pop the first item from  $H$ 
(12)     $a \leftarrow a - \omega_{i,z}^- * \lambda_1 * \lambda_2 * b$ 
(13)    if  $a > 0$ 
(14)       $r_{i,z} \leftarrow r_{i,z} + \frac{1}{n_i}$ 
(15)    else
(16)       $r_e \leftarrow 1 + \frac{a}{\lambda_1 * \lambda_2 * \omega_{i,z}^- * b}$ 
(17)       $r_{i,z} \leftarrow r_{i,z} + \frac{r_e}{n_i}$ 
(18)    return
(19)    if  $j < n_i$ 
(20)       $v_{i,s_i^{j+1}} \leftarrow u_{i,z} * n_i * o_{i,s_i^{j+1}} / \sum_{k=1}^{n_i} o_{i,k}$ 
(21)      insert  $v_{i,s_i^{j+1}}$  into  $H$ 

```

$\lambda_1 * \lambda_2 * \omega_{i,z}^- * b * u_{i,z} * p_{i,s_i^z} * n_i$  units (which is the utility gained per time unit, from comparing incoming tuples of type  $z$  with tuples in  $B_{i,j}$ ). The aim is to pick maximum number of items, where fractional items are acceptable, so that the total value is maximized and the total volume of the picked items is at most  $\lambda_1 * \lambda_2 * r * (w_2 + w_1)$ .  $r_{i,j,z} \in [0, 1]$  is used to denote how much of item  $I_{i,j,z}$  is picked. Note that the number of unknown variables here ( $r_{i,j,z}$ 's) is  $(n_1 + n_2) * |\mathcal{Z}|$ , and the solution of the original problem can be calculated from these variables as,  $r_{i,z} = \sum_{j=1}^{n_i} r_{i,j,z}$ .

The values of the fraction variables are determined during join direction adaptation. A simple way to do this, is to sort the items based on their value over volume ratios,  $v_{i,j,z} = u_{i,z} * p_{i,s_i^z} * n_i$  (note that  $o_{i,j} / \sum_{k=1}^{n_i} o_{i,k}$  can be used as an estimate of  $p_{i,s_i^z}$ ), and to pick as much as possible of the item that is most valuable per unit volume. However, since the number of items is large, the sort step is costly, especially for large number of basic windows and large sized domains. A more efficient solution, with worst case complexity  $\mathcal{O}(|\mathcal{Z}| + (n_1 + n_2) * \log |\mathcal{Z}|)$ , is described in Algorithm 5, which replaces Algorithm 4. Algorithm 5 makes use of the  $s_i^z$  values that define an order between value over volume ratios of items for a fixed type  $z$  and window  $W_i$ . The algorithm keeps the items representing different streams and types with the highest value over volume ratios ( $2 * |\mathcal{Z}|$  of them), in a heap. It iteratively picks an item from the heap and replaces it with the item having the next highest value over volume ratio with the same stream and type subscript index. This process continues until the capacity constraint is reached. During this process  $r_{i,z}$  values are calculated progressively. If the item picked represents window  $W_i$  and type  $z$ , then  $r_{i,z}$  is incremented by  $1/n_i$  unless the item is picked fractionally, in which case the increment on  $r_{i,z}$  is adjusted accordingly.

## 6. EXPERIMENTS

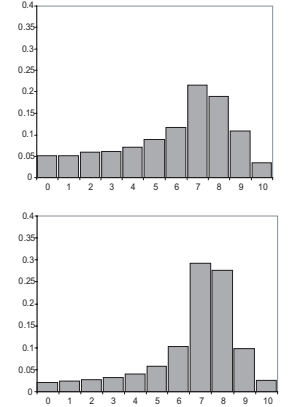
We report four sets of experimental results to demonstrate effectiveness of the algorithms introduced in this paper. The first set illustrates the need for shedding CPU load for both indexed (using inverted indexes) and non-indexed joins. The second set demonstrates the performance provided by the

partial processing-based load shedding step – keeping tuples within windows and shedding excessive load by partially processing the join through rate adaptation. The third set shows the performance gain in terms of output rate for selective processing, which incorporates time correlation adaptation and join direction adaptation. The effect of basic window size on the performance is also investigated experimentally. The fourth set of experiments presents results on the utility-based load shedding mechanisms introduced and their ability to maximize output utility under different workloads.

### 6.1 Experimental Setup

The join operation is implemented as a Java package, named `ssjoin.*`, and is customizable with respect to supported features, such as rate adaptation, time correlation adaptation, join direction adaptation, and utility-based load shedding, as well as various parameters associated with these features. Streams used in the experiments reported in this section are timestamp ordered tuples, where each tuple includes a single attribute, that can either be a set, or weighted set. The sets are composed of variable number of items, where each item is an integer in the range  $[1..L]$ .  $L$  is taken as 100 in the experiments. Number of items contained in sets follow a normal distribution with mean  $\mu$  and standard deviation  $\sigma$ . In the experiments,  $\mu$  is taken as 5 and  $\sigma$  is taken as 1. The popularity of items in terms of how frequent they occur in a set, follows a Zipf distribution with parameter  $\kappa$ . The time based correlation between streams is modeled using two parameters, *time shift* parameter denoted as  $\tau$  and *cycle period* parameter denoted as  $\varsigma$ .

Cycle period is used to change the popularity ranks of items as a function of time. Initially at time 0, the most popular item is 1, the next 2, and so on. Later at time  $T$ , the most popular item is  $a = 1 + \lfloor L * \frac{T \bmod \varsigma}{\varsigma} \rfloor$ , the next  $a + 1$ , and so on. Time shift is used to introduce a delay between matching items from different streams. Applying a time shift of  $\tau$  to one of the streams means that the most popular item is  $a = 1 + \lfloor L * \frac{(T - \tau) \bmod \varsigma}{\varsigma} \rfloor$  at time  $T$ , for that stream. Figure 5 shows the resulting probability of match distribution  $f_1$ , when a time delay of  $\tau = \frac{5}{8} * \varsigma$  is applied to stream  $S_2$  and  $\varsigma = 2 * w$ , where  $w_1 = w_2 = w$ .



**Figure 5: Probability match distributions,  $\kappa = 0.6$  and  $\kappa = 0.8$**

The two histograms represent two different scenarios, in which  $\kappa$  is taken as 0.6 and 0.8, respectively. These settings for  $\tau$  and  $\varsigma$  parameters are also used in the rest of the experiments, unless otherwise stated. We change the value of parameter  $\kappa$  to model varying amounts of skewness in match probability distributions. Experiments are performed using time varying stream rates and various window sizes. The default settings of some of the system parameters are as follows:  $T_r = 5$  seconds,  $T_c = 5$  seconds,  $\delta_r = 1.2$ ,  $\gamma = 0.1$ . We report results from overlap join operations. Other types of joins show similar results. The experiments are performed on an IBM PC with 512MB main memory and 2.4Ghz Intel Pentium 4 processor, using Sun JDK 1.4.2.

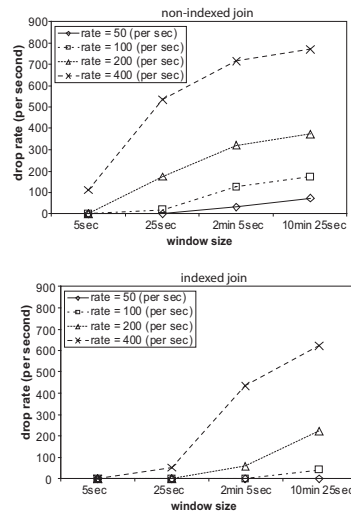
### 6.2 Processing Power Limitation

We first validate that the processing power happens to be the limiting resource, for both indexed and non-indexed join operations. Graphs in Figure 6 plot tuple drop rates (sum of the drop rates of the two streams) for non-indexed (left) and indexed joins (right), as a function of window size for different stream rates. The join operation performed is an overlap join with threshold value of 3. It is observed from the figure that, for a non-indexed join, even a low stream rate of 50 tuples per second results in dropping approximately half of the tuples, when the window size is set to 125 seconds. This corresponds to a rather small window size of around 150 KBytes, when compared to the total memory available. Although indexed join improves performance by decreasing tuple drop rates, it is only effective for moderate window sizes and low stream rates. A stream rate of 100 tuples per second results in dropping approximately one quarter of the tuples for a 625 seconds window (approx. 10 minutes). This corresponds to a window size of around 1.5 MBytes. As a result, CPU load shedding is a must for costly stream joins.

### 6.3 Rate Adaptation

We study the impact of rate adaptation on output rate of the join operation. For the purpose of the experiments in this subsection, time shift parameter is set to zero, i.e.  $\tau = 0$ , so that there is no time shift between the streams and the match probability decreases going from the beginning of the windows to the end. A non-indexed overlap join, with threshold value of 3 and 20 seconds window on one of the streams, is used. Figure 7 shows the stream rates used (on the left  $y$ -axis) as a function of time. The rate of the streams stay at 100 tuples per second for around 60 seconds, then jump to 500 tuples per seconds for around 15 seconds and drop to 300 tuples per second for around 30 seconds before going back to its initial value. Figure 7 also shows (on the right  $y$ -axis) how fraction parameter  $r$  adapts to the changing stream rates. The graph in Figure 8 shows the resulting stream output rate as a function of time with and without rate adaptation. No rate adaptation represents random tuple dropping. It is observed that rate adaptation improves output rate when the stream rates increase. That is the time when tuple dropping starts for the non-adaptive case. The improvement is around 100% when stream rates are 500 tuples per second and around 50% when 300 tuples per second. The ability of rate adaptation to keep output rate high is mainly due to the time aligned nature of the streams. In this scenario, only the tuples that are closer to the beginning of the window are useful for generating matches and the partial processing uses the beginning part of the window, as dictated by the fraction parameter  $r$ .

The graph in Figure 9 plots the average output rate of the



**Figure 6: Tuple drop rates for non-indexed and indexed join operations, as a function of window size, with varying stream rates**

join over the period shown in Figure 8 as a function of skewness parameter  $\kappa$ , for different window sizes. It shows that the improvement in output rate, provided by rate adaptation, increases not only with increasing skewness of the match probability distribution, but also with increasing window sizes. This is because, larger windows imply that more load shedding has to be performed.

### 6.4 Selective Processing

We study the impact of time correlation adaptation and join direction adaptation on output rate of the join operation. For the purpose of the experiments in this subsection, time shift parameter is taken as  $\tau = \frac{5}{8} * \zeta$ . A non-indexed overlap join, with threshold value of 3 and 20 seconds windows on both of the streams, is used. Basic window sizes on both windows are set to 1 second for time correlation adaptation. Figure 10 shows the stream rates used (on the left  $y$ -axis) as a function of time. Figure 10 also shows (on the right  $y$ -axis) how fraction parameters  $r_1$  and  $r_2$  adapt to the changing stream rates with join direction adaptation. Note that the reduction in fraction parameter values start with the one ( $r_2$  in this case) corresponding to the window that is less useful in terms of generating output tuples when processed against a newly fetched tuple from the other stream. The graph in Figure 11 shows the resulting stream output rate as a function of time with three different join settings. It is observed that, when the stream rates increase, the time correlation adaptation combined with rate adaptation provides improvement on output rate (around 50%), when compared to rate adaptation only case. Moreover, applying join direction adaptation on top of time correlation adaptation provides additional improvement in output rate (around 40%).

The graph in Figure 12 plots the average output rate of the join as a function of skewness parameter  $\kappa$ , for different join settings. This time, the overlap threshold is set to 4, which results in lower number of matching tuples. It is observed that the improvement in output rate, provided by time correlation and join direction adaptation, increases with increasing skewness in match probability distribution. The increasing skewness does not improve the performance of rate adaptive only case, due to its lack of time correlation adaptation which in turn makes it unable to locate the productive portion of the window for processing, especially when the time lag  $\tau$  is large and the fraction parameter  $r$  is small.

#### 6.4.1 Basic Window Size

We study the impact of basic window size on output rate of the join operation. The graphs in Figure 13 plot average join output rate as a function of basic window size, for different  $\kappa$  values. The graph on the left represents a non-indexed overlap join, with threshold value of 3 and 20 seconds windows on both of the streams. The graph on the right represents an indexed overlap join, with threshold value of 3 and 20 seconds windows on both of the streams. For the indexed case, both identifier sorted and time sorted inverted indexes are used. “none” value on the  $x$ -axis of the graphs represent the case where basic windows are not used (note that this is *not* same as using a basic window equal in size to join window). For both experiments, a stream rate of 500 tuples per second is used.

As expected, small basic windows provide higher join output rate. However, there are two interesting observations for the indexed join case. First, for very small basic window sizes, we observe a drop in the output rate. This is due to the

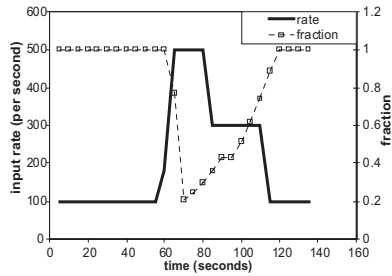


Figure 7: Stream rates and fraction parameter  $r$

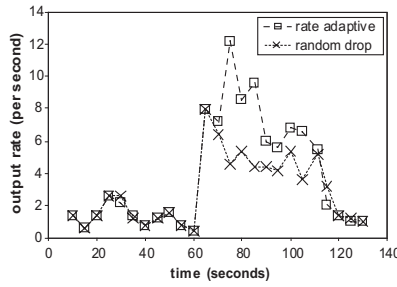


Figure 8: Improvement in output rate with rate adaptation

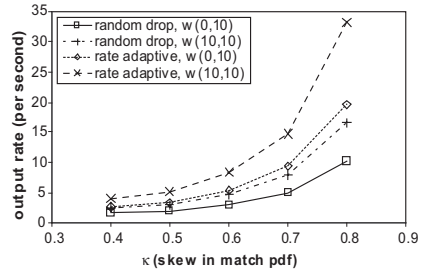


Figure 9: Improvement in average output rate with rate adaptation

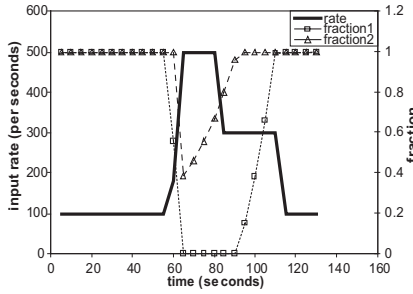


Figure 10: Stream rates and fraction parameters  $r_1$  and  $r_2$

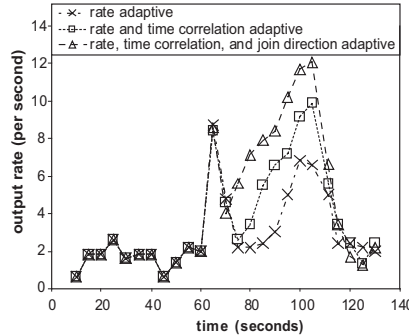


Figure 11: Improvement in output rate with time correlation and join direction adaptation

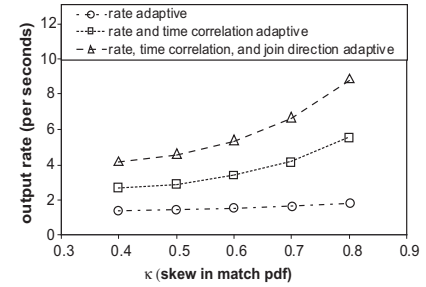


Figure 12: Improvement in average output rate with time correlation and join direction adaptation

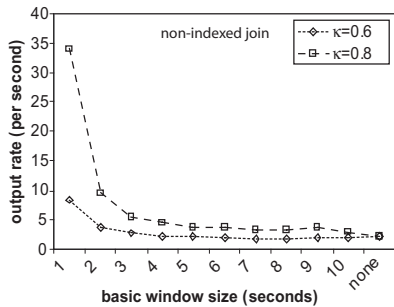


Figure 13: Impact of basic window size for indexed and non-indexed join, for various basic window sizes

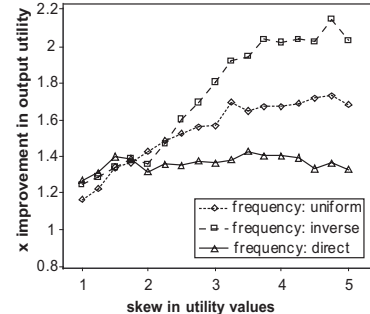
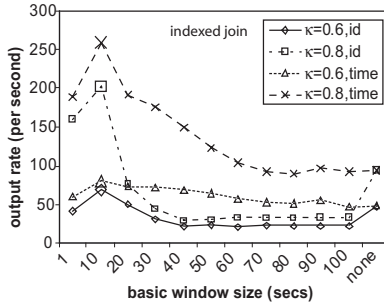


Figure 14: Improvement in output utility for different type frequency models

overhead of processing large number of basic windows with indexed join. In particular, the cost of looking up identifier lists for each basic window that is used for join processing, creates an overhead. Further decreasing basic window size does not help in better capturing the peak of the match probability distribution. Second, identifier sorted inverted indexes show significantly lower output rate, especially when the basic window sizes are high. This is because identifier sorted inverted indexes do not allow partial processing based on time.

## 6.5 Utility-based Load Shedding

We study the effectiveness of utility-based load shedding in improving output utility of the join operation. We consider three different scenarios in terms of setting type frequencies; (i) uniform, (ii) inversely proportional to utility values, and (iii) directly proportional to utility values. For the experiments in this subsection, we use a non-indexed overlap join, with threshold value of 3 and 20 seconds windows on both of the streams. 500 tuples per second is used as the stream rate.

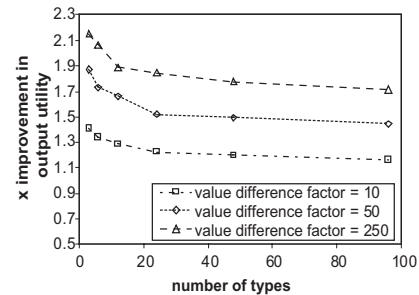


Figure 15: Output utility improvement for different type domain sizes

The graph in Figure 14 plots the improvement in output utility of the join, compared to the case where no utility-based load shedding is used, as a function of skewness in utility values. Both joins are rate, time correlation, and join direction adaptive. In this experiment, there are three different tuple

types, i.e.  $|\mathcal{Z}| = 3$ . For a skewness value of  $k$ , the utility values of the types are  $\{1, 1/2^k, 1/3^k\}$ . It is observed from the figure that, the improvement in output utility increases with increasing skewness for uniform and inversely proportional type frequencies, where it stays almost stable for directly proportional type frequencies. Moreover, the best improvement is provided when item frequencies are inversely proportional to utility values. Note that this is the most natural case, as in most applications, rare items are of higher interest.

The graph in Figure 15 studies the effect of domain size on the improvement in output utility. It plots the improvement in output utility as a function of type domain size, for different *value difference factors*. A value difference factor of  $x$  means the highest utility value is  $x$  times the lowest utility value and the utility values follow a Zipf distribution (with parameter  $\log_{|\mathcal{Z}|} x$ ). The type frequencies are selected as inversely proportional to utility values. It is observed from the figure that, there is an initial decrease in output utility improvement with increasing type domain size. But the improvement values stabilize quickly as the type domain size gets larger. Same observation holds for different amounts of skewness in utility values.

## 7. CONCLUSION

We have presented an adaptive load shedding approach for costly stream join operations over tuples with set-valued or weighted set-valued attributes. A stream join over these types of tuples tends to be CPU-intensive. In particular, we showed how rate adaptation, combined with time based correlation adaptation and join direction adaptation, can increase the number of output tuples produced by a join operation. Our load shedding algorithms employed a selective processing approach, as opposed to commonly used tuple dropping. This enabled our algorithms to nicely integrate utility-based load shedding with time correlation based load shedding in order to improve output utility of the join for the applications where some tuples are evidently more valued than others. Our experimental results illustrated the effectiveness of our adaptive load shedding algorithms under varying input stream rates, varying CPU load conditions, and varying time correlations between the streams.

## 8. REFERENCES

- [1] A. Arasu, B. Babcock, S. Babu, M. Datar, K. Ito, R. Motwani, I. Nishizawa, U. Srivastava, D. Thomas, R. Varma, and J. Widom. STREAM: The stanford stream data manager. *IEEE Data Engineering Bulletin*, 26, March 2003.
- [2] B. Babcock, S. Babu, M. Datar, R. Motwani, and J. Widom. Models and issues in data stream systems. In *ACM PODS*, 2002.
- [3] B. Babcock, S. Babu, R. Motwani, and M. Datar. Chain: operator scheduling for memory minimization in data stream systems. In *ACM SIGMOD*, 2003.
- [4] B. Babcock, M. Datar, and R. Motwani. Load shedding for aggregation queries over data streams. In *IEEE ICDE*, 2004.
- [5] H. Balakrishnan, M. Balazinska, D. Carney, U. Cetintemel, M. Cherniack, C. Convey, E. Galvez, J. Salz, M. Stonebraker, N. Tatbul, R. Tibbetts, and S. Zdonik. Retrospective on Aurora. *VLDB Journal Special Issue on Data Stream Processing*, 2004.
- [6] D. Carney, U. Cetintemel, M. Cherniack, C. Convey, S. Lee, G. Seidman, M. Stonebraker, N. Tatbul, and S. Zdonik. Monitoring streams: A new class of data management applications. In *VLDB*, 2002.
- [7] S. Chandrasekaran, O. Cooper, A. Deshpande, M. J. Franklin, J. M. Hellerstein, W. Hong, S. Krishnamurthy, S. R. Madden, V. Raman, F. Reiss, and M. A. Shah. TelegraphCQ: Continuous dataflow processing for an uncertain world. In *CIDR*, 2003.
- [8] S. Chandrasekaran and M. J. Franklin. Remembrance of streams past: Overload-sensitive management of archived streams. In *VLDB*, 2004.
- [9] A. Das, J. Gehrke, and M. Riedewald. Approximate join processing over data streams. In *ACM SIGMOD*, 2003.
- [10] L. Golab, S. Garg, and M. T. Ozsu. On indexing sliding windows over online data streams. In *EDBT*, 2004.
- [11] L. Golab and M. T. Ozsu. Processing sliding window multi-joins in continuous queries over data streams. In *VLDB*, 2003.
- [12] M. A. Hammad and W. G. Aref. Stream window join: Tracking moving objects in sensor-network databases. In *Scientific and Statistical Database Management, SSDBM*, 2003.
- [13] S. Helmer, T. Westmann, and G. Moerkotte. Diag-Join: An opportunistic join algorithm for 1:N relationships. In *VLDB*, 1998.
- [14] J. Kang, J. Naughton, and S. Viglas. Evaluating window joins over unbounded streams. In *IEEE ICDE*, 2003.
- [15] J. Kleinberg. Bursty and hierarchical structure in streams. In *ACM SIGKDD*, 2002.
- [16] R. Korfhage. *Information Storage and Retrieval*. Wiley, May 1997.
- [17] S. R. Madden, M. J. Franklin, J. M. Hellerstein, and W. Hong. TAG: a Tiny AGgregation service for ad-hoc sensor networks. In *USENIX OSDI*, 2002.
- [18] N. Mamoulis. Efficient processing of joins on set-valued attributes. In *ACM SIGMOD*, 2003.
- [19] R. Motwani, J. Widom, A. Arasu, B. Babcock, S. Babu, M. Datar, G. Manku, C. Olston, J. Rosenstein, and R. Varma. Query processing, resource management, and approximation in a data stream management system. In *CIDR*, 2003.
- [20] S. Helmer and G. Moerkotte. Evaluation of main memory join algorithms for joins with subset join predicates. In *VLDB*, 1997.
- [21] U. Srivastava and J. Widom. Flexible time management in data stream systems. In *ACM PODS*, 2004.
- [22] U. Srivastava and J. Widom. Memory-limited execution of windowed stream joins. In *VLDB*, 2004.
- [23] N. Tatbul, U. Cetintemel, S. Zdonik, M. Cherniack, and M. Stonebraker. Load shedding in a data stream manager. In *VLDB*, 2003.
- [24] P. A. Tucker, D. Maier, T. Sheard, and L. Fegaras. Exploiting punctuation semantics in continuous data streams. *IEEE Transactions on Knowledge and Data Engineering*, 15, 2003.
- [25] K.-L. Wu, S.-K. Chen, and P. S. Yu. Interval query indexing for efficient stream processing. In *ACM CIKM*, 2004.