Double Index NEsted-loop Reactive Join for Result Rate Optimization

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***Abstract*— Adaptive join algorithms have recently attracted a lot of attention in emerging applications where data is provided by autonomous data sources through heterogeneous network environments. Their main advantage over traditional join techniques is that they can start producing join results as soon as the first input tuples are available, thus improving pipelining by smoothing join result production and by masking source or network delays. In this paper we propose Double Index NEsted-loops Reactive join (DINER), a new adaptive join algorithm for result rate maximization. DINER combines two key elements: an intuitive flushing policy that aims to increase the productivity of in-memory tuples in producing results during the online phase of the join, and a novel re-entrant join technique that allows the algorithm to rapidly switch between processing in-memory and disk-resident tuples, thus better exploiting temporary delays when new data is not available. Our experiments using real and synthetic data sets demonstrate that DINER outperforms previous adaptive join algorithms in producing result tuples at a significantly higher rate, while making better use of the available memory.**

I. Introduction

Modern information processing is moving into a realm where we often need to process data that is pushed or pulled from autonomous data sources through heterogeneous networks. Adaptive query processing has emerged as an answer to the problems that arise because of the fluidity and unpredictability of data arrivals in such environments [1]. An important line of research in adaptive query processing has been towards developing join algorithms that can produce tuples "online", from streaming, partially available input relations, or while waiting for one or both inputs [3], [6], [9], [12], [14]. Such non-blocking join behavior can improve pipelining by smoothing or "masking" varying data arrival rates and can generate join results with high rates, thus improving performance in a variety of query processing scenarios in data integration, on-line aggregation and approximate query answering systems.

Compared to traditional join algorithms (be they sort-, hash- or nested loops-based [13]), adaptive joins are designed to deal with some additional challenges: The input relations they use are provided by external network sources. The implication is that they have little or no control in the order or rate of arrival of tuples. Since the data source reply speed, streaming rate and streaming order, as well as network traffic and congestion levels, are unpredictable, traditional join algorithms are often unsuitable or inefficient. For example, most traditional join algorithms cannot produce results until one or both relations are completely available. Waiting for one relation to arrive completely to produce results is often unacceptable. Moreover, and more importantly, in emerging data integration or online aggregation environments, a key performance metric is rapid availability of first results and a continuous rate of tuple production.

Adaptive join algorithms were created in order to lift the limitations of traditional join algorithms in such environments. By being able to produce results whenever input tuples become available, adaptive join algorithms overcome situations like initial delay, slow data delivery or bursty arrival, which can affect the efficiency of the join. All existing algorithms work in three stages. During the *Arriving* phase, a newly arrived tuple is stored in memory and it is matched against memory-resident tuples belonging to the opposite relation. Since the allocated memory for the join operation is limited and often much smaller than the volume of the incoming data, this results in tuple migration to disk. The decision on what to flush to disk influences largely the number of results produced during the Arriving phase. The Arriving phase is suspended when both data sources are temporarily blocked and a *Reactive* phase kicks in and starts joining part of the tuples that have been flushed to disk. An important desideratum of this phase is the prompt handover to the Arriving phase as soon as any of the data sources restarts sending tuples. Each algorithm has a handover delay which depends on the minimum unit of work that needs to be completed before switching phases. This delay has not received attention in the past, but we show that it can easily lead to input buffer overflow, lost tuples and hence incorrect results. When both sources complete the data transmission, a *Cleanup* phase is activated and the tuples that were not joined in the previous phases (due to flushing of tuples to disk) are brought from disk and joined.

In this paper, we propose *Double Index NEsted-loop Reactive* join (DINER), a new join algorithm for output rate maximization in data processing over autonomous distributed

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sources. DINER follows the same overall pattern of execution as previous algorithms but incorporates a series of novel techniques and ideas that make it faster, leaner (in memory use) and more adaptive than its predecessors. The key difference between DINER and existing algorithms is (1) an intuitive flushing policy for the Arriving phase that aims at maximizing the amount of overlap of the join attribute values between tuples of the two relations and (2) a lightweight Reactive phase that allows the algorithm to quickly move into processing tuples that were flushed to disk when both data sources block.

The key idea of our flushing policy is to create and adaptively maintain three non-overlapping value regions that partition the join attribute domain, measure the "join benefit" of each region at every flushing decision point, and flush tuples from the region that doesn't produce many join results in a way that permits easy maintenance of the 3-way partition of the values. As it will be explained, proper management of the three partitions allows us to increase the number of tuples with matching values on their join attribute from the two relations, thus maximizing the output rate. When tuples are flushed to disk they are organized into sorted blocks using an efficient index structure, maintained separately for each relation (thus the part "Double Index" in DINER). This optimization results in faster processing of these tuples during the Reactive and Cleanup phases. The Reactive phase of DINER employs a symmetric nested loop join process, combined with novel bookkeeping that allows the algorithm to react to the unpredictability of the data sources. The fusion of the two techniques allows DINER to make much more efficient use of available main memory. We demonstrate in our experiments that DINER has a higher rate of join result production and is much more adaptive to changes in the environment, including changes in the value distributions of the streamed tuples and in their arrival rates.

An important feature of DINER is that it is the first adaptive, completely unblocking join technique that supports range join conditions. Range join queries are a very common class of joins in a variety of applications, from traditional business data processing to financial analysis applications and spatial data processing. Progressive Merge Join [3] (PMJ), one of the early adaptive algorithms, also supports range conditions, but its blocking behavior makes it a poor solution given the requirements of current data integration scenarios. Our experiments indeed show that PMJ is outperformed by DINER.

The contributions of our paper are:

- We introduce DINER a novel adaptive join algorithm that supports both equality and range join predicates. DINER builds on a intuitive flushing policy that aims at maximizing the productivity of tuples that are kept in memory.
- DINER is the first algorithm to address the need to quickly respond to bursts of arriving data during the Reactive phase. We propose a novel extension to nested loops join for processing disk-resident tuples when both sources block, while being able to swiftly respond to new data arrivals.
- We provide a thorough discussion on existing algorithms, including identifying some important limitations, such as increased memory consumption because of their inability to quickly switch to the Arriving phase and not being responsive enough when value distributions change.
- We provide an extensive experimental study, including performance comparisons to existing adaptive join algorithms and a sensitivity analysis. Our results demonstrate the superiority of DINER in a variety of realistic scenarios. During the online phase of the algorithm, DINER manages to produce up to three times more results compared to previous techniques. The performance gains of DINER are realized when using both real and synthetic data and are increased when fewer resources (memory) are given to the algorithm.

The rest of the paper is organized as follows. Section II presents prior work in the area. In Section III we introduce the DINER algorithm and discuss in detail its operations. In Section IV we present our experiments, while in Section V we draw concluding remarks.

II. Related Work

Adaptive join algorithms were designed for producing results as fast as the input tuples become available and also for overcoming the penalty induced when one or both data sources experience delays. Existing work on adaptive join techniques can be classified in two groups: hash-based [5], [6], [9], [14], [12] and sort-based [3]. Examples of hash based algorithms include DPHJ [6] and XJoin [14], the first of a new generation of adaptive non-blocking join algorithms to be proposed. XJoin was inspired by Symmetric Hash Join (SHJ) [5], which represented the first step towards avoiding the blocking behavior of the traditional hash-based algorithms. SHJ required both relations to fit in memory, however XJoin removes this restriction. The above mentioned algorithms were proposed for data integration and online aggregation. Pipelined hash join [15], developed concurrently with SHJ, is also an extention of hash join and was proposed for pipelined query plans in parallel main memory environment.

Algorithms based on sorting were generally blocking, since the original sort merge join algorithm required an initial sorting on both relations before the results could be obtained. Although there were some improvements that attenuate the blocking effect [10], the first efficient non-blocking sort-based algorithm was Progressive Merge Join (PMJ) [3].

Hash Merge Join (HMJ) [9], based on XJoin and PMJ, is a non-blocking algorithm which tries to combine the best parts of its predecessors while avoiding their shortcomings. Finally, Rate-based Progressive Join (RPJ) [12] is an improved version of HMJ that is the first algorithm to make decisions, e.g., about flushing to disk, based on the characteristics of the data.

In what follows we describe the main existing techniques for adaptive join. For all hash-based algorithms, we assume that each relation R_i, $i = A, B$ is organized in n_{part} buckets. The presentation is roughly chronological.

XJoin. As with "traditional" hash based algorithms, XJoin organizes each input relation in an equal number of memory and disk partitions or buckets, based on a hash function applied

on the join attribute. XJoin extends SHJ so that it can be applied on larger data sets.

The XJoin algorithm operates in three phases. During the first, *arriving*, phase, which runs for as long as either of the data sources sends tuples, the algorithm joins the tuples from the memory partitions. Each incoming tuple is stored in its corresponding bucket and is joined with the matching tuples from the opposite relation. When memory gets exhausted, the partition with the greatest number of tuples is flushed to disk. The tuples belonging to the bucket with the same designation in the opposite relation remain on disk. When both data sources are blocked, the first phase pauses and the second, *reactive*, phase begins. The last, *cleanup*, phase starts when all tuples from both data sources have completely arrived. It joins the matching tuples that were missed during the previous two phases.

In XJoin the reactive stage can run multiple times for the same partition. Thus, a duplicate avoidance strategy is necessary in order to detect already joined tuple pairs during subsequent executions. XJoin adds two timestamps called arrival timestamp (ATS) and departure timestamp (DTS) to the tuple structure. The algorithm still has to detect the tuple pairs joined during the reactive phase and avoid repeating these joins. XJoin deals with these potential duplicates by creating a timestamp list associated with each disk partition, recording the time when the second phase was applied to the partition. DINER borrows the general concept of timestamps for duplicate avoidance from XJoin, and improves upon it. For example, due to our use of block-ids and sorting, as described in Section III-D, we can do away with the timestamp list.

Progressive Merge Join. PMJ is the adaptive non-blocking version of the sort merge join algorithm. It splits the memory into two partitions. As tuples arrive, they are inserted in their memory partition. When the memory gets full, the partitions are sorted on the join attribute and are joined using any memory join algorithm. Thus, output tuples are obtained each time the memory gets exhausted. Next, the *partition pair* (i.e., the bucket pairs that were simultaneously flushed each time the memory was full) is copied on disk. After the data from both sources completely arrives, the merging phase begins. The algorithm defines a parameter F, the maximal fan-in, which represents the maximum number of disk partitions that can be merged in a single "turn". $F/2$ groups of sorted partition pairs are merged in the same fashion as in sort merge. In order to avoid duplicates in the merging phase, a tuple joins with the matching tuples of the opposite relation only if they belong to a different partition pair.

Hash Merge Join. HMJ [9] is a hybrid query processing algorithm combining ideas from XJoin and Progressive Merge Join. HMJ has two phases, the hashing and the merging phase. The hashing phase performs in the same way XJoin (and also DPHJ [6]) perform, except that when memory gets full, a flushing policy decides which pair of corresponding buckets from the two relations is flushed on disk. The flushing policy uses a heuristic that again does not take into account data characteristics: it aims to free as much space as possible while keeping the memory balanced between both relations. Keeping the memory balanced helps to obtain a greater number of results during the hashing phase. Unlike the other hash-based algorithms, HMJ uses fewer disk buckets than memory buckets: the hashing phase has better performance with more buckets (and smaller bucket size), while the merging phase performs better with fewer large disk buckets. Consecutive memory buckets that are flushed go in the same disk bucket. Every time HMJ flushes the current contents of a pair of buckets, they are sorted and create a disk bucket "segment"; this way the first step in a subsequent sort merge phase is already performed.

When both data sources get blocked or after complete data arrival, the merging phase kicks in. It essentially applies a sort-merge algorithm where the sorted sublists (the "segments") are already created. The sort-merge algorithm is applied on each disk bucket pair and it is identical to the merging phase of PMJ. As described earlier, each disk bucket contains a number of sorted segments, written on disk at each memory flush, which represent the input of sort merge join. Duplicates are avoided during the merging phase by ensuring that the matching tuples belonging to the same sorted segment pair do not join.

Rate-based Progressive Join. RPJ [12] is the most recent and advanced adaptive join algorithm. It is the first algorithm that tries to understand and exploit the connection between the memory content and the algorithm output rate. During the online phase it performs as HMJ. When memory is full, it tries to estimate which tuples have the smallest chance to participate in joins.

Its flushing policy is based on the estimation of $p_i^{arr}[j]$, the probability of a new incoming tuple to belong to relation R_i and to be part of bucket j. Once all probabilities are computed, the flushing policy is applied. Let $p_i^{arr}[j]$ be the smallest probability. In this case, n_{flush} tuples belonging to bucket j of the opposite relation are spilled. If the victim bucket does not contain enough tuples, the next smallest probability is chosen, etc. All the tuples that are flushed together from the same relation and from the same bucket are sorted and they form a sorted "segment" as in HMJ.

In case both relations are temporarily blocked, RPJ begins its reactive phase, which "combines" the XJoin and HMJ reactive phases. The tuples from one of the disk buckets of either relation can join with the corresponding memory bucket of the opposite relation, as in case of XJoin, or two pairs of disk buckets can be brought in memory and joined as in case of HMJ (and PMJ). The algorithm chooses the task that has the highest output rate. During its cleanup phase RPJ joins the disk buckets. The duplicate avoidance strategy is similar with the one applied by XJoin.

The following important observation applies to the reactive phase algorithm run by both HMJ and RPJ. When a "disk to disk" process takes place, the algorithm checks for new incoming tuples after a set of F segments belonging to each

	Symbol	Description ($i \in \{A, B\}$)
General	R_i	Input relation R_i
	t_i	Tuple belonging to relation R_i
	$Index_i$	Index for relation R_i
	$Disk_i$	Disk partition containing flushed tuples of relation R_i
	UsedMemory	Current amount of memory occupied by tuples, indexes and statistics
	MemThresh	Maximum amount of available memory to the algorithm
	WaitThresh	Maximum time to wait for new data before switching to Reactive phase
Statistics	$LastLwVal_i$ $LastUpVal_i$	Thresholds for values of join attribute in lower and upper regions of R_i
	$LwJoins_i$ $MdJoins_i$ $UpJoins_i$	Number of produced joins by tuples in the lower, middle and upper region, correspondingly, of R_i
	$LwTups_i$ $MdTups_i$ $UpTups_i$	Number of in-memory tuples in the lower, middle and upper region, correspondingly, of R_i
	$BfLw_i$ $BfMd_i$ $BfUp_i$	Benefit of in-memory tuples in the lower, middle and upper region, correspondingly, of R_i

TABLE I
SYMBOLS USED IN OUR ALGORITHM

bucket pair are merged, where F is the fan-in parameter of PMJ. The drawback is that after consecutive runs of this phase over the same pair of disk buckets, the progressively merged segments have larger and larger sizes and their merge takes longer; meanwhile, incoming tuples are ignored. So the algorithm stays in its reactive phase longer, possibly generating additional join results, but at the price of requiring a much larger input buffer to store incoming tuples, which otherwise might have to be dropped, compromising the algorithm's correctness.

III. ALGORITHM DESCRIPTION

We now present our *Double Index NEsted-loop Reactive join* (DINER) algorithm for computing the join result of two finite relations R_A and R_B, which may be stored at potentially different sites and are streamed to our local system. Given the unpredictable behavior of the network, delays and random temporary suspensions in data transmission may be experienced. The goal of DINER is twofold. It first seeks to correctly produce the join result, by quickly processing arriving tuples, while avoiding operations that may jeopardize the correctness of the output because of memory overflow. Moreover, in the spirit of prior work [4], [9], [12] the DINER algorithm seeks to increase the number of join tuples (or, equivalently, the rate of produced results) generated during the online phase of the join, i.e., during the (potentially long) time it takes for the input relations to be streamed to our system. To achieve these goals, DINER is highly adaptive to the (often changing) value distributions of the relations, as well as to potential network delays.

Table I summarizes the main notation used in the presentation of the DINER algorithm. Additional definitions are presented in appropriate areas of the text.

A. Algorithm Overview

Algorithm Internals and Data Structures. Incoming tuples from both relations share the available memory. A separate index $Index_i$ ($i \in \{A, B\}$) on the join attribute is maintained for the memory resident part of each input relation. In our implementation we utilize a Judy [2] structure, which is maintained in memory. The Judy tree was selected as it combines very small memory footprint with fast lookups and the ability to have sorted access based on the index keys – any main memory index structure with these space and data access characteristics can be used, such as an in-memory B-tree. The total amount of memory, denoted as UsedMemory, used by our algorithm is upper-bounded by the value MemThresh. The value of UsedMemory includes in its computation the memory occupied by the input buffer (stage where incoming tuples arrive), the in-memory tuples being processed by the algorithm, the Judy indices and any additional data structures utilized by DINER for maintaining statistics.

Finally, each relation is associated with a disk partition, $Disk_A$ and $Disk_B$, which stores the tuples from the relation that do not fit in memory and have been flushed to disk. The memory and disk blocks used by the DINER algorithm are selected to be multiples of the operating system block size so that the disk I/O operations can be performed efficiently.

Format of Stored Tuples. Each tuple inserted in memory is augmented with an arriving timestamp (ATS). Each tuple flushed to disk is further augmented with a departure timestamp (DTS). As explained later in this section, these timestamps are used in order to ensure that during the Reactive and Cleanup phases every pair of tuples between the two relations will be examined exactly once, thus ensuring the correctness of the produced result.

Each tuple residing in main memory is also augmented with a *join bit*.[1] This bit is initially set to 0. Whenever an in-memory tuple helps produce a join result, its join bit is set to 1. As described in Section III-C, the join bits are utilized by a process responsible for evicting tuples that do not produce joins from some areas of the memory. The latter process seeks to evict those tuples that have their join bit set to 0, while clearing the join bit of the tuples that it examines. Those tuples that have produced joins in the past will eventually have their join bit cleared and get evicted at a subsequent invocation of the process, if at some point they stop producing join results. Thus, the join bit serves as a 1-bit approximation to LRU, similarly to the clock algorithm for buffer page replacement [11]. Maintaining a counter (instead of a single join bit) for the number of joins that each tuple has produced would have been more accurate. However, such an approach would also consume more space. We decided to use the join bit after experimentally evaluating both alternatives.

Phases of the Algorithm. The operation of DINER is divided into three phases, termed in this paper as the *Arriving*, *Reactive* and *Cleanup* phases. While each phase is discussed in more

[1]The join bit is actually part of the index entry for the tuple.

Algorithm 1 Arriving Phase

```
1: if R_A and R_B have been received completely then
2:    Run Cleanup Phase
3:    return
4: else if transmission of R_A and R_B is blocked more than WaitThresh then
5:    Run Reactive Phase
6: else if t_i ∈ R_i arrived (i ∈ {A, B}) then
7:    Move t_i from input buffer to DINER process space.
8:    Augment t_i with join bit and arrival timestamp ATS
9:    j = {A, B} − i      {Refers to "opposite" relation}
10:   matchSet = set of matching tuples (found using Index_j) from opposite
      relation R_j
11:   joinNum = |matchSet|   (number of produced joins)
12:   if joinNum > 0 then
13:      Set the join bits of t_i and of all tuples in matchSet
14:   else
15:      Clear the join bit of t_i
16:   end if
17:   UpdateStatistics(t_i, joinNum)
18:   indexOverhead = Space required for indexing t_i using Index_i
19:   while UsedMemory+indexOverhead ≥ MemThresh do
20:      Apply flushing policy      (see Algorithm 3)
21:   end while
22:   Index t_i using Index_i
23:   Update UsedMemory
24: end if
25: goto 1
```

Algorithm 2 UpdateStatistics

```
Require: t_i (i ∈ {A, B}), numJoins
1: j = {A, B} − i      {Refers to the opposite relation}
2: JoinAttr ← t_i.JoinAttr
3: {Update statistics on corresponding region of relation R_i}
4: if JoinAttr ≥ LastUpVal_i then
5:    UpJoins_i ← UpJoins_i + numJoins
6:    UpTups_i ← UpTups_i + 1
7: else if JoinAttr ≤ LastLwVal_i then
8:    LwJoins_i ← LwJoins_i + numJoins
9:    LwTups_i ← LwTups_i + 1
10: else
11:   MdJoins_i ← MdJoins_i + numJoins
12:   MdTups_i ← MdTups_i + 1
13: end if
14: {Update statistics of opposite relation}
15: if JoinAttr ≥ LastUpVal_j then
16:   UpJoins_j ← UpJoins_j + numJoins
17: else if JoinAttr ≤ LastLwVal_j then
18:   LwJoins_j ← LwJoins_j + numJoins
19: else
20:   MdJoins_j ← MdJoins_j + numJoins
21: end if
```

detail in what follows, we note here that the Arriving phase covers operations of the algorithm while tuples arrive from one or both sources, the Reactive phase is triggered when both relations block and, finally, the Cleanup phase finalizes the join operation when all data has arrived to our site.

B. Arriving Phase

Tuples arriving from each relation are initially stored in memory and processed as described in Algorithm 1. The Arriving phase of DINER runs as long as there are incoming tuples from at least one relation. When a new tuple t_i is available, all matching tuples of the opposite relation that reside in main memory are located and used to generate result tuples as soon as the input data is available. When matching tuples are located, the join bits of those tuples are set, along with the join bit of the currently processed tuple (Line 13). Then, some statistics need to be updated (Line 17). This procedure will be described later in this section.

When the MemThresh is exhausted, the flushing policy (discussed in Section III-C) picks a *victim* relation and memory-resident tuples from that relation are moved to disk in order to free memory space (Lines 19-21). The number of flushed tuples is chosen so as to fill a disk block. The flushing policy may also be invoked when new tuples arrive and need to be stored in the input buffer (Line 6). Since this part of memory is included in the budget (MemThresh) given to the DINER algorithm, we may have to flush other in-memory tuples to open up some space for the new arrivals. This task is executed asynchronously by a server process that also takes care of the communication with the remote sources. Due to space limitations, it is omitted from presentation.

If both relations block for more than WaitThresh msecs (Lines 4-5) and, thus, no join results can be produced, then the algorithm switches over to the Reactive phase, discussed in Section III-D. Eventually, when both relations have been received in their entirety (Line 2), the Cleanup phase of the algorithm, discussed in Section III-E, helps produce the remaining results.

C. Flushing Policy and Statistics Maintenance

An overview of the algorithm implementing the flushing policy of DINER is given in Algorithm 3. In what follows we describe the main points of the flushing process.

Selection of Victim Relation. As in prior work, we try to keep the memory balanced between the two relations. When the memory becomes full, the relation with the highest number of in-memory tuples is selected as the *victim* relation (Line 1).

Intuition. The algorithm should keep in main memory those tuples that are most likely to produce results by joining with subsequently arriving tuples from the other relation.

Unlike prior work that tries to model the distribution of values of each relation [12], our premise is that real data is often too complicated and cannot easily be captured by a simple distribution, which we may need to predetermine and then adjust its parameters. We have, thus, decided to devise a technique that aims to maximize the number of joins produced by the in-memory tuples of both relations by adjusting the tuples that we flush from relation R_A (R_B), based on the range of values of the join attribute that were recently obtained by relation R_B (R_A), and the number of joins that these recent tuples produced.

For example, if the values of the join attribute in the incoming tuples from relation R_A tend to be increasing and these new tuples generate a lot of joins with relation R_B, then this is an indication that we should try to flush the tuples from relation R_B that have the smallest values on the join attribute (of course, if their values are also smaller than those of the tuples of R_A) and vise versa. The net effect of this intuitive policy is that memory will be predominately occupied by tuples from both relations whose range of values on the join attribute overlap. This will help increase the number of joins produced in the online phase of the algorithm.

Simply flushing tuples from the two endpoints (higher and lower values of the join attribute) does not always suffice, as it could allow tuples with values of the join attribute close

Algorithm 3 Flushing Policy

1: Pick as victim the relation R_i ($i \in \{A, B\}$) with the most in-memory tuples
2: {Compute benefit of each region}
3: $BfUp_i$=$UpJoins_i/UpTups_i$
4: $BfLw_i$=$LwJoins_i/LwTups_i$
5: $BfMd_i$=$MdJoins_i/MdTups_i$
6: {$Tups\_Per\_Block$ denotes the number of tuples required to fill a disk block}
7: **if** $BfUp_i$ is the minimum benefit **then**
8: locate $Tups\_Per\_Block$ tuples with the larger join attribute using $Index_i$
9: flush the block on $Disk_i$
10: update $LastUpVal_i$ so that the upper region is (about) a disk block
11: **else if** $BfLw_i$ is the minimum benefit **then**
12: locate $Tups\_Per\_Block$ tuples with the smaller join attribute using $Index_i$
13: flush the block on $Disk_i$
14: update $LastLwVal_i$ so that the lower region is (about) a disk block
15: **else**
16: Using the Clock algorithm, visit the tuples from the middle area, using $Index_i$, until $Tups\_Per\_Block$ tuples are evicted.
17: **end if**
18: Update $UpTups_i$, $LwTups_i$, $MdTups_i$, when necessary
19: $UpJoins_i$,$LwJoins_i$,$MdJoins_i \leftarrow 0$

to its median to remain in main memory for a long time, without taking into account their contribution in producing join results. Thus, a technique that removes from main memory such potentially "unproductive" tuples is essential.

Conceptual Tuple Regions. The DINER algorithm accounts (and maintains statistics) for *each* relation for three conceptual regions of the in-memory tuples: the lower, the middle and the upper region. These regions are determined based on the value of the join attribute for each tuple.

The three regions are separated by two conceptual boundaries: $LastLwVal_i$ and $LastUpVal_i$ for each relation R_i that are dynamically adjusted during the operation of the DINER algorithm. In particular, all the tuples of R_i in the lower (upper) region have values of the join attribute smaller (larger) or equal to the $LastLwVal_i$ ($LastUpVal_i$) threshold. All the remaining tuples are considered to belong in the middle in-memory region of their relation.

Maintained Statistics. The DINER algorithm maintains simple statistics in the form of six counters (two counters for each conceptual region) for each relation. These statistics are updated during the Arriving phase as described in Algorithm 2. We denote by $UpJoins_i$, $LwJoins_i$ and $MdJoins_i$ the number of join results that tuples in the upper, lower and middle region, respectively, of relation R_i have helped produce. These statistics are reset every time we flush tuples of relation R_i to disk (Algorithm 3, Line 19). Moreover, we denote by $UpTups_i$, $LwTups_i$ and $MdTups_i$ the number of in-memory tuples of R_i that belong to the conceptual upper, lower and middle region, respectively, of relation R_i. These numbers are updated when the boundaries between the conceptual regions change (Line 18).

Where to Flush From. Once a victim relation R_i has been chosen, the victim region is determined based on a benefit computation. We define the *benefit* $BfLw_i$ of the lower region of R_i to be equal to:

$$BfLw_i = \frac{LwJoins_i}{LwTuples_i}$$

The corresponding benefit $BfUp_i$ and $BfMd_i$ for the upper and middle regions of R_i are defined in a completely analogous manner (Lines 3-5). Given these (per space) benefits, the DINER algorithm decides to flush tuples from the region exhibiting the smallest benefit.

How to Flush from Each Region. When the DINER algorithm determines that it should flush tuples from the lower (upper) region, it starts by first flushing the tuples in that region with the lowest (highest) values of the join attribute and continues towards higher (lower) values until a disk block has been filled (Lines 7-15). This process is expedited using the index. After the disk flush, the index is used to quickly identify the minimum $LastLwVal_i$ (maximum $LastUpVal_i$) values such that the lower (upper) region contains enough tuples to fill a disk block. The new $LastLwVal_i$ and $LastUpVal_i$ values will identify the boundaries of the three regions until the next flush operation.

When flushing from the middle region (Line 16), we utilize a technique analogous to the Clock [11] page replacement algorithm. At the first invocation, the *hand* of the clock is set to a random tuple of the middle region. At subsequent invocations, the hand recalls its last position and continues from there in a round-robin fashion. The hand continuously visits tuples of the middle region and flushes those tuples that have their join bit set to 0, while resetting the join bit of the other visited tuples. The hand stops as soon as it has flushed enough tuples in order to fill a disk block.

A special case occurs when the algorithm flushes data from each relation for the very first time. In this case, the $LastLwVal_i$ and $LastUpVal_i$ values have not been previously set. Thus, at the first time our algorithm (i) considers all the tuples of each relation to belong to its middle region and flushes from that area; and (ii) using the index, which can provide sorted access to the data, quickly identifies $LastLwVal_i$ and $LastUpVal_i$ values such that each of the lower and upper regions contain enough tuples to fill a disk block.

The expelled tuples from either relation are organized in sorted blocks by accessing the memory using the victim's index. Thus, tuples that are flushed to disk in the same operation are sorted based on the join attribute. This is done in order to speed up the execution of the Reactive and Cleanup phases of the algorithm, discussed later in this section.

Implementation Details. In situations where the data is extremely skewed, the middle region may get entirely squeezed. In such rare cases we make sure that the $LastLwVal_i$ and $LastUpVal_i$ values never create overlapping intervals for the lower and upper regions (i.e., the invariant $LastLwVal_i < LastUpVal_i$ always holds). In such extremely skewed data (i.e., all the data having the same key value), one region may end up containing almost all of the tuples, thus raising the possibility that a flushed region may actually contain fewer tuples than the ones required to fill a disk block. In such situations the DINER algorithm continues applying its flushing policy to the region with the second (and possible even the third) highest (per space) benefit until enough tuples have been flushed to disk.

Importance of Upper, Middle and Lower Regions. While

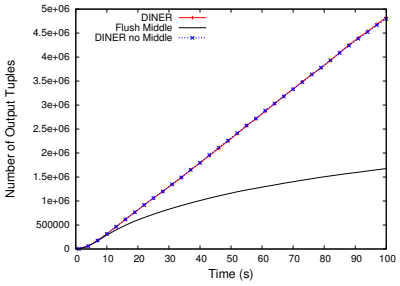

Fig. 1. Performance of Variants with a=0.0

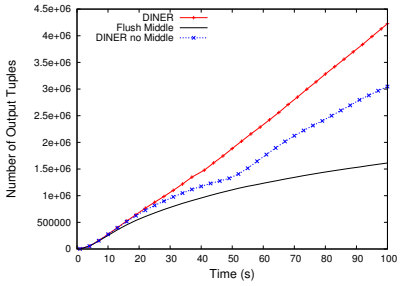

Fig. 2. Performance of Variants with a=0.1

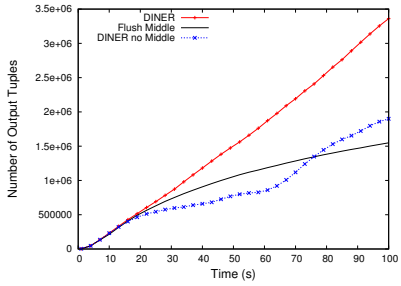

Fig. 3. Performance of Variants with a=0.2

in the experimental section we compare DINER to other state of the art algorithms, we present here an experiment that demonstrates the importance of maintaining the three regions in our algorithm and the impact of our flushing policy. We thus compare our DINER algorithm against two variants. The DINER *no Middle* technique is identical to DINER, but never flushes from the middle region. On the other hand, the *Flush Middle* technique considers the *entire* memory to be a single region and always flushes from that region. This case is analogous to using the Clock algorithm.

We created a synthetic data set, where the data distribution of the join attribute of both relations follows a normal distribution with a mean value equal to the middle value of the domain (i.e., the most frequent value lies in the middle of the domain). Thus, the values near the endpoints of the domain for both relations are encountered with the smallest probabilities.

In Figures 1, 2 and 3 we show how our DINER algorithm performs, in terms of the number of tuples produced during the online phase, against the two tested variants, when in the aforementioned data set we have also imposed an additional condition: we prevent the most frequent values of the two relations, those that lie within a fraction a of the distribution's variance from the mean value, to join. Thus, $a = 0$ corresponds to the imposition of no additional condition on the join values, while increasing values of a widen the area around the mean where joins are not produced, even though tuples from both relations exist in that area. Even though this condition is imposed artificially, such situations, where the distributions of data are similar or even the same but the most frequent values aren't exactly the same, and hence don't join, can arise.

As expected, for $a = 0$ the correct decision is to flush the tuples having join attribute values near the endpoints of the domain. Thus, DINER performs identically to DINER *no Middle*. While a increases, the performance of DINER *no Middle* deteriorates (and may become worse than *Flush Middle*), since it is now more efficient to flush from main memory the tuples near the mean of the distribution that do not join. The DINER algorithm, based on the benefit computation over the three regions, clearly shows its superiority over the two alternatives that only flush tuples from the end-points or from the middle region, respectively.

D. Reactive Phase

The Reactive phase join algorithm, termed ReactiveNL, is a nested loops-based algorithm that runs whenever both relations are blocked. It performs joins between previously flushed data from both relations that are kept in the disk partitions $Disk_A$ and $Disk_B$, respectively. This allows DINER to make progress while no input is being delivered. The algorithm switches back to the Arriving phase as soon as enough, but not too many, input tuples have arrived, as is determined by the value of input parameter MaxNewArr. The goal of ReactiveNL is to perform as many joins between flushed-to-disk blocks of the two relations as possible, while simplifying the bookkeeping that is necessary when exiting and re-entering the Reactive phase.

Symbol	Description
OuterSize	Size of outer relation in blocks
InnerSize	Size of inner relation in blocks
OuterMem	#fetched disk blocks from outer relation at each step
MaxOuterMem	Maximum allowed value of OuterMem
JoinedOuter	Last outer block that has joined with inner relation up to JoinedInner
JoinedInner	Last inner block that has joined with outer relation up to JoinedOuter
CurrInner	Inner block being joined with latest chunk of OuterMem outer-blocks
MaxNewArr	Maximum number of tuples accumulated in the input buffer before exiting Reactive Phase

TABLE II
NOTATION USED IN THE REACTIVENL ALGORITHM

Algorithm ReactiveNL is presented in Algorithm 4. We assume that each block of tuples flushed on disk is assigned an increasing block-id, for the corresponding relation (i.e., the first block of relation R_A corresponds to block 1, the second to block 2 etc). The notation used in the algorithm is available in Table II. Figures 4 and 5 provide a helpful visualization of the progress of the algorithm. Its operation based on the following points.

Point 1. ReactiveNL initially selects one relation to behave as the outer relation of the nested loop algorithm, while the other relation initially behaves as the inner relation (Lines 1-3). Notice that the "inner relation" (and the "outer") for the purposes of ReactiveNL consists of the blocks of the corresponding relation that currently reside on disk, because they were flushed during the Arriving phase.

Point 2. ReactiveNL tries to join successive batches of OuterMem blocks of the outer relation with all of the inner relation, until the outer relation is exhausted (Lines 13-20). The value of OuterMem is determined based on the maximum number of blocks the algorithm can use (input parameter

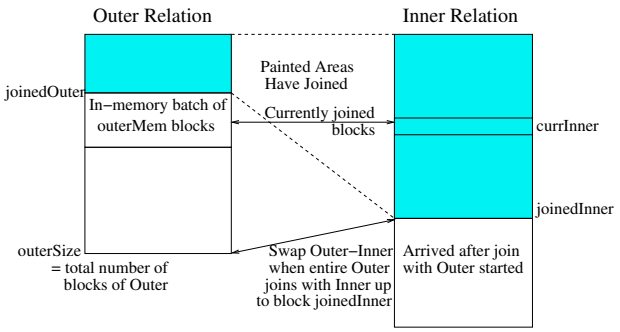

Fig. 4. Status of the algorithm during the reactive phase.

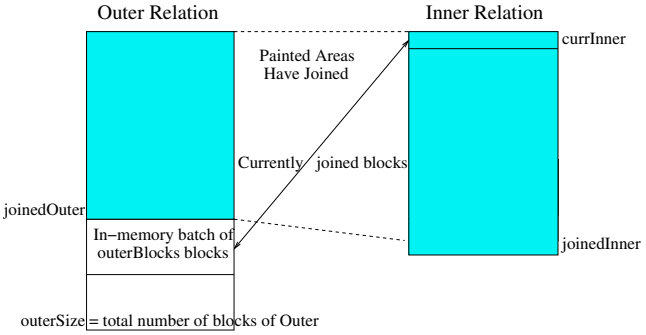

Fig. 5. Status of algorithm after swapping the roles of the two relations.

Algorithm 4 ReactiveNL

```
Require: MaxOuterMem, MaxNewArr
 1: if First Algorithm Invocation then
 2:    Set Outer← smallest(Disk_A,Disk_B)
 3:    Set Inner← largest(Disk_A,Disk_B)
 4:    Set JoinedInner to size of Inner Relation
 5:    Set JoinedOuter to 0 and CurrInner to 1
 6: end if{Else the old parameter values are used}
 7: while unprocessed blocks exist do
 8:    while JoinedOuter<OuterSize do
 9:       {Load next chunk of outer blocks. CurrInner reveals whether some blocks
          from the outer relation had started joining with the inner relation, but did not
          complete this task.}
10:       if CurrInner== 1 then
11:          OuterMem= min(MaxOuterMem, OuterSize-JoinedOuter)
12:       end if{Else keep its previous value}
13:       Load OuterMem blocks from outer relation starting with block-id Joined-
          Outer+1. If not sufficient space in memory, apply flushing policy to clear up
          enough space.
14:       while CurrInner≤JoinedInner do
15:          Load CurrInner block of inner relation in memory and join with in-
             memory outer blocks based on join attribute and non-overlapping ATS..DTS
             timestamps
16:          CurrInner←CurrInner+1
17:          if Input buffer size greater than MaxNewArr then
18:             Break;
19:          end if
20:       end while
21:       if CurrInner>JoinedInner then
22:          {Mark completed join of [1..JoinedOuter] and [1..JoinedInner] blocks}
23:          JoinedOuter←JoinedOuter+OuterMem
24:          CurrInner←1
25:       end if
26:       if Input buffer size greater than MaxNewArr then
27:          {Switch back to Arriving Phase}
28:          exit
29:       end if
30:       if JoinedOuter==OuterSize then
31:          Change roles between inner and outer
32:       end if
33:    end while
34: end while
```

MaxOuterMem) and the size of the outer relation. However, as DINER enters and exits the Reactive phase, the size of that inner relation may change, as more blocks of that relation may be flushed to disk. To make it easier to keep track of joined blocks, we need to join each batch of OuterMem blocks of the outer relation with the same, fixed number of blocks of the inner relation – even if over time the total number of disk blocks of the inner relation increases. One of the key ideas of ReactiveNL is the following: at the first invocation of the algorithm, we record the number of blocks of the inner relation in JoinedInner (Line 4). From then on, all successive batches of OuterMem blocks of the outer relation will only join with the first JoinedInner blocks of the inner relation, until all the available outer blocks are exhausted.

Point 3. When the outer relation is exhausted (Lines 30-32), there may be more than JoinedInner blocks of the inner relation on disk (those that arrived after the first round of the nested loop join, when DINER goes back to the Arriving phase). If that is the case, then these new blocks of the inner relation need to join with all the blocks of the outer relation. To achieve this with the minimum amount of bookkeeping, it is easier to simply switch roles between relations, so that the inner relation (that currently has new, unprocessed disk blocks on disk) becomes the outer relation and vice versa (all the counters change roles also, hence JoinedInner takes the value of JoinedOuter etc, while CurrInner is set to point to the first block of the *new* inner relation). Thus, an invariant of the algorithm is that the tuples in the first JoinedOuter blocks of the outer relation have joined with all the tuples in the first JoinedInner blocks of the inner relation.

Point 4. To ensure prompt response to incoming tuples, and to avoid overflowing the input buffer, after each block of the inner relation is joined with the in-memory OuterMem blocks of the outer relation, ReactiveNL examines the input buffer and returns to the Arriving phase if more than MaxNewArr tuples have arrived. (We do not want to switch between operations for a single tuple, as this is costly). The input buffer size is compared at Lines 17-19 and 26-28, and if the algorithm exits, the variables JoinedOuter, JoinedInner and CurrInner keep the state of the algorithm for its next re-entry. At the next invocation of the algorithm, the join continues by loading (Lines 9-13) the outer blocks with ids in the range [JoinedOuter+1,JoinedOuter+OuterMem] and by joining them with inner block CurrInner.

Point 5. As was discussed earlier, the flushing policy of DINER spills on disk full blocks with their tuples sorted on the join attribute. The ReactiveNL algorithm takes advantage of this data property and speeds up processing by performing an in-memory sort merge join between the blocks. During this process, it is important that we do not generate duplicate joins between tuples t_{outer} and t_{inner} that have already joined during the Arriving phase. This is achieved by proper use of the ATS and DTS timestamps. If the time intervals $[t_{outer}.ATS,\ t_{outer}.DTS]$ and $[t_{inner}.ATS,\ t_{inner}.DTS]$ overlap, this means that the two tuples co-existed in memory during the Arriving phase and their join is already obtained. Thus, such pairs of tuples are ignored by

the ReactiveNL algorithm (Line 15).

Discussion. The Reactive phase is triggered when both data sources are blocked. Since network delays are unpredictable, it is important that the join algorithm is able to quickly switch back to the Arriving phase, once data starts flowing in again, otherwise we risk overflowing the input buffer. Previous adaptive algorithms [9], [12], which also include such a Reactive phase, have some conceptual limitations, dictated by a minimum amount of work that needs to be performed during the Reactive phase, that prevent them from promptly reacting to new arrivals. For example, as discussed in Section II, during its Reactive phase, the RPJ algorithm works on progressively larger partitions of data. Thus, a sudden burst of new tuples while the algorithm is on its Reactive phase quickly leads to large increases in input buffer size and buffer overflow, as shown in the experiments presented in Section IV. One can potentially modify the RPJ algorithm so that it aborts the work performed during the Reactive phase or keeps enough state information so that it can later resume its operations in case the input buffer gets full, but both solutions have not been explored in the literature and further complicate the implementation of the algorithm. In comparison, keeping the state of the ReactiveNL algorithm only requires three variables, due to our novel adaptation of the traditional nested loops algorithm.

E. Cleanup Phase

The Cleanup phase starts once both relations have been received in their entirety. It continues the work performed during the Reactive phase by calling the ReactiveNL algorithm. In this case, one block of memory is kept for the inner relation and the rest of the blocks are allocated for the outer by properly setting the OuterMem parameter.

IV. EXPERIMENTS

In this section, we present an extensive experimental study of our proposed DINER algorithm. The objective of this study is twofold. We first evaluate the performance of DINER against the state of the art HMJ [9] and RPJ [12] algorithms for a variety of both real-life and synthetic data sets. We also ran experiments using the DPHJ and XJoin algorithms but they are both dominated in performance by RPJ and/or HMJ. For brevity and clarity in the figures, we have decided to include their performance only in few of the figures presented in this section and omit them for the rest. We also investigate the impact that several parameters may have on the performance of the DINER algorithm, through a detailed sensitivity analysis. The main findings of our study include:

• **A Faster Algorithm.** DINER provides result tuples at a significantly higher rate, up to 3 times in some cases, than existing adaptive join algorithms during the online phase. This also leads to a faster computation of the overall join result when there are bursty tuple arrivals.

• **A Leaner Algorithm.** The DINER algorithm further improves its relative performance to the compared algorithms in terms of produced tuples during the online phase in more constrained memory environments. This is mainly attributed to our novel flushing policy.

• **A More Adaptive Algorithm.** The DINER algorithm has an even larger performance advantage over existing algorithms, when the values of the join attribute are streamed according to a non stationary process. Moreover, it better adjusts its execution when there are unpredictable delays in tuple arrivals, to produce more result tuples during such delays.

• **Suitable for Range Queries.** The DINER algorithm can also be applied to joins involving range conditions for the join attribute. This is a unique characteristic when compared to existing non-blocking algorithms, since they all operate by hashing the tuples based on their join attribute values and are, thus, only applicable to equijoins. PMJ [3] also supports range queries but, as shown in our experimental section, it is a generally poor choice since its performance is limited by its blocking behavior.

Parameter Settings. The following settings are used during the experimental section: The tuple size is set to 200 bytes and the disk block size is set to 10KB. The inter-arrival delay (i.e., the delay between two consecutive incoming tuples), unless specified otherwise, is modelled using an exponential distribution with parameter $\lambda = 0.1$.

The memory size allocated for all algorithms is 5% of the total input size, unless otherwise specified. All incoming unprocessed tuples are stored in the input buffer, whose size is accounted for in the total memory made available to the algorithms.

Real Data Sets. In our experimental evaluation we utilized two real data sets. The Stock data set contains traces of stock sales and purchases over a period of one day. From this data set we extracted the transactions relating to the IPIX and CSCO stocks.[2] For each stock we generated one relation based on the part of the stock traces involving buy orders, and a second relation based on the part of the stock traces that involve sells. The size of CSCO stream is 20,710 tuples while the size of IPIX stream is 45,568 and the tuples are equally split among the relations. The join attribute used was the price of the transaction. We also used a Weather data set containing meteorological measurements from two different weather stations.[3] We populated two relations, each from the data provided by one station, and joined them on the value of the air temperature attribute. Each relation in the Weather data set contains 45,000 tuples.

Since the total completing time of the join for all algorithms is comparable, in most of the cases the experiments show the outcome for the online phase (i.e., until tuples are completely received from the data sources).

All the experiments were performed on a machine running Linux with an Intel processor clocked at 1.6 GHz and with 1 GB of memory. All algorithms were implemented in C++. For RPJ, also implemented in C++, we used the code that the authors of [12] have made available.

[2]From http://cs-people.bu.edu/jching/icde06/ExStockData.tar

[3]From http://www-k12.atmos.washington.edu/k12/grayskies/nw_weather.html

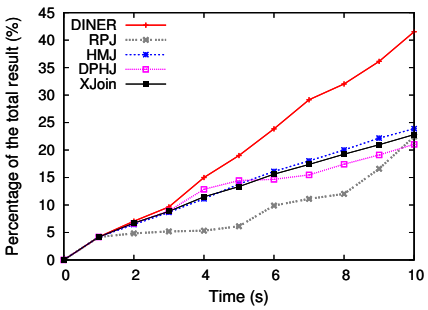

Fig. 6. CSCO data set

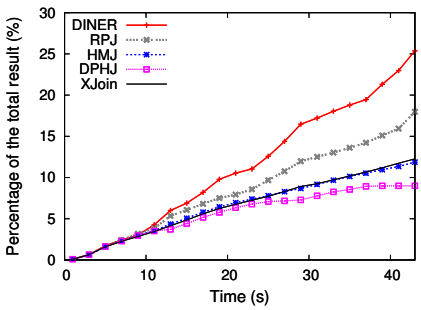

Fig. 7. Weather data set

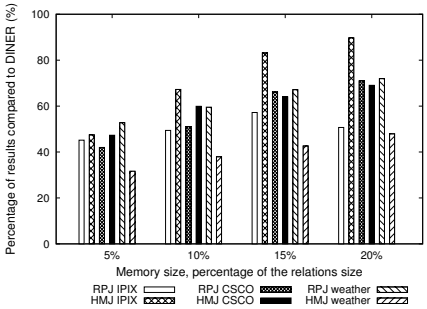

Fig. 8. Real data, different memory size

A. Overall Performance Comparison

In the first set of experiments, we demonstrate DINER's superior performance over a variety of real and synthetic data sets in an environment without network congestion or unexpected source delays.

In Figures 6, 7 we plot the cumulative number of tuples produced by the join algorithms over time, during the online phase for the CSCO stock and the Weather data sets. We observe that DINER has a much higher rate of tuples produced that all other competitors. For the stock data, while RPJ is not able to produce a lot of tuples initially, it manages to catch up with XJoin at the end.

In Figure 8 we compare DINER to RPJ and HMJ on the real data sets when we vary the amount of available memory as a percentage of the total input size. The y axis represents the tuples produced by RPJ and HMJ at the end of their *online phase*, (i.e., until the two relations have arrived in full) as a percentage of the number of tuples produced by DINER over the same time. The DINER algorithm significantly outperforms RPJ and HMJ, producing up to 2.5 times more results than the competitive techniques. The benefits of DINER are more significant when the size of the available memory given to the join algorithms is reduced.

In the next set of experiments we evaluate the performance of the algorithms when synthetic data is used. In all runs, each relation contains 100,000 tuples. In Figure 9, the values of the join attribute follow a Zipf distribution in the interval $[1, 999]$ and the skew parameter is varied from 1 to 5, with the leftmost value (i.e., value 1) exhibiting the highest probability of occurrence in each case. We observe that the benefits of DINER are even larger than in the real data.

In Figures 10 and 11 the join attribute follows the normal distribution. In the first figure, the join attribute of the first relation has a normal distribution with mean 500 and variance 50, while, the join attribute of the second relation is normally distributed, with variance 50 and mean equal to $500 + x$. Thus, by increasing the value of x (x-axis) we increase the degree of separation between the two distributions. For the experiments in Figure 11 the first relation is the same as in Figure 10, while the mean of the second relation is 500 but, this time, the variance is modeled as $50 + x$, where x is the value on the x axis. We observe that the larger the divergence between the two distributions, the larger the benefits of DINER when compared to RPJ and HMJ. The increase in the benefit is more evident when the mean value varies (Figure 10) and is largely attributed to the flushing policy that cleans up unproductive tuples between the mean values of the two distributions (middle region). In contrast, for the experiment in Figure 11, the distributions have the same mean value and most of the flushed tuples come from the upper and lower regions of DINER. These findings complement the results we presented in Section III-C, which demonstrated that the advantages of DINER stem from the synergy of these regions based on our benefit computation.

The above experiments demonstrate that DINER adapts better to different distributions of the join attribute, as shown in Figures 9, 10 and 11.

Range Predicates. In Figure 12 we present experimental results for range joins on the Stock and Weather data sets. The streams for the two relations are formed as described earlier, with the exception of the join conditions: A pair of tuples from the Stock data set joins if their price difference is smaller than 5 cents. For the Weather data set, each relation contains environmental information from a specific location and two tuples join if their temperature difference is smaller than 5 degrees. The y axis of Figure 12 shows the fraction of the overall result that was obtained during the online phase of DINER and PMJ. The memory size is set at 5% of the total input size. We note that RPJ and HMJ do not support such join predicates, since they are hash-based.

B. Non Stationary Data Streaming Processes

The DINER algorithm adapts quickly to situations where the value distribution of the join attribute changes over time. We present two experiments that demonstrate DINER's superior performance in such situations. In Figure 13 the input relations are streamed partially sorted as follows: The frequency of the join attribute is determined by a zipf distribution with values between $[1, 999]$ and skew 1. The data is sorted and divided in a number of "intervals", shown on the x axis. The ordering of the intervals is permuted randomly and the resulting relation is streamed. The benefits of DINER are significant in all cases.

In the second experiment, shown in Figure 14, we divide the total relation transmission time in 10 periods of $10sec$ each. In each transmission period, the join attributes of both relations are normally distributed, with variance equal to 15, but the mean is shifted upwards from period to period. In particular,

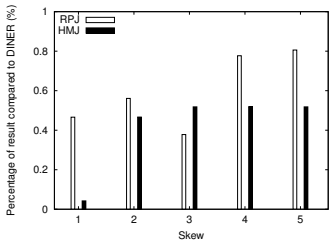

Fig. 9. Zipf distribution with different skew parameters, memory 5% of input size

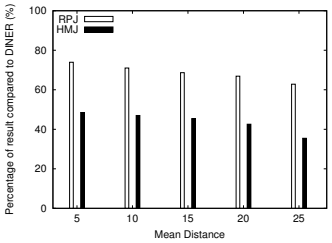

Fig. 10. Normal distribution, different mean

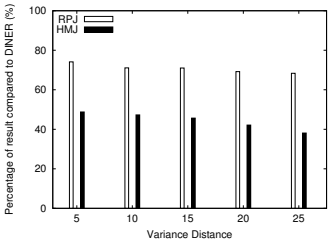

Fig. 11. Normal distribution, different variance

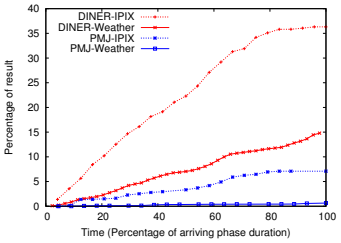

Fig. 12. Range Join Queries

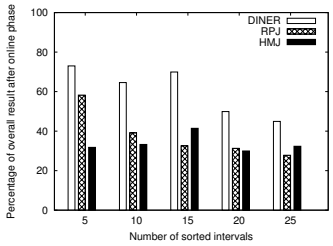

Fig. 13. Zipf distribution, partially sorted data

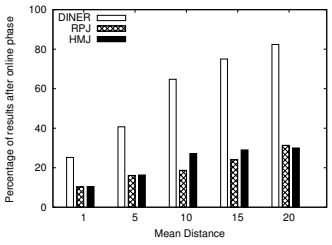

Fig. 14. Nonstationary normal, changing means

the mean in period i is $75 + i * shift$, where $shift$ is the value on the x axis. We can observe that the DINER algorithm produces up to 3 times more results during the online phase than RPJ and HMJ, with its relative performance difference increasing as the distribution changes more quickly.

C. Network/Source Delays

The settings explored so far involve environments where tuples arrive regularly, without unexpected delays. In this section we demonstrate that DINER is more adaptive to unstable environments affecting the arriving behavior of the streamed relations. DINER uses the delays in data arrival, by joining tuples that were skipped due to flushes on disk, while being able to hand over to the Arriving phase quickly, when incoming tuples are accumulated in the input buffer.

In Figure 15, the streamed relations' join attributes follow a zipf distribution with a skew parameter of 1. The interarrival time is modelled in the following way: Each incoming relation contains 100,000 tuples and is divided in 10 "fragments". Each fragment is streamed using the usual exponential distribution of inter-tuple delays with $\lambda = 0.1$. After each fragment is transmitted, a delay equal to $x\%$ of its transmission time is introduced (x is the parameter varied in the x axis of the figure). If the delays of both relations happen to overlap to some extent, all algorithms enter the Reactive phase, since they all use the same triggering mechanism dictated by the value of parameter WaitThresh, which was set to 25msecs. For this experiments, DINER returns to the Arriving phase when 1,000 input tuples have accumulated in the input buffer (input parameter MaxNewArr in Algorithm 4). The value of the input parameter MaxOuterMem in the same algorithm was set to 19 blocks. The parameter F for RPJ discussed in Section II was set to 10, as in the code provided by the authors of [12] and for HMJ to 10, which had the best performance in our experiments for HMJ. We observe that DINER generates

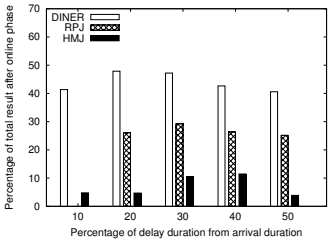

Fig. 15. Zipf distribution, delay duration is a percentage of the "burst" duration

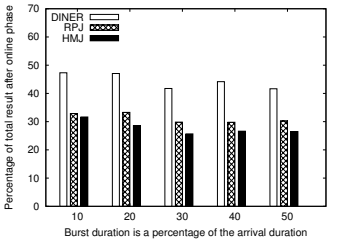

Fig. 16. CSCO stock data, delay duration is a percentage of the "burst" duration

	Inter-Arrival Delay (% of transmission time)				
Buffer Size	10 %	20 %	30 %	40 %	50 %
DINER Max	1030	1009	1008	1008	1004
DINER Avg	930	987	988	1001	1001
RPJ Max	**40000**	6548	6016	3422	2719
RPJ Avg	**40000**	3204	2880	1723	1377
HMJ Max	1443	423	2939	8269	7144
HMJ Avg	440	117	671	3356	2423

TABLE III
INPUT BUFFER SIZE FOR ZIPF DATA DURING REACTIVE PHASE

	Memory (% of input size)			
Data Set	5 %	10 %	15 %	20 %
CSCO	28 %	43 %	49 %	58 %
IPIX	38 %	59 %	72 %	82 %
Weather	10 %	17%	24 %	29 %

TABLE IV
PERCENTAGE OF THE TOTAL RESULT OBTAINED FOR DINER DURING ONLINE PHASE FOR DIFFERENT MEMORY SIZE

up to 1.83 times more results than RPJ when RPJ does not overflow and up to 8.65 times more results than HMJ.

The value of the input parameter MaxNewArr is correlated with the number of memory blocks that are used during the intermediate phase. After the reactive phase is finished, the memory allocated to this phase can be reused so that the algorithm can efficiently deal with the tuples accumulated in the input buffer and this observation justifies our choice for the input buffer threshold.

We notice that for the smaller delay duration, the RPJ algorithm overflows its input buffer and, thus, cannot complete the join operation. In Table III we repeat the experiment allowing the input buffer to grow beyond the memory limit during the Reactive phase and present the maximum size of the input buffer during the Reactive phase.

We also experimented with the IPIX and CSCO stock data. The inter-tuple delay is set as in the previous experiment. The results for the CSCO data are presented in Figure 16, which show the percentage of tuples produced by RPJ and HMJ compared to the tuples produced by DINER at the end of the online phase. The graph for the IPIX data is qualitatively similar and is omitted due to lack of space.

From the above experiments, the following conclusions can be drawn:

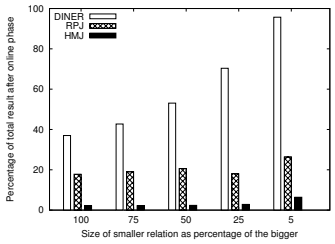

Fig. 17. Zipf Distribution, Different Relation Size

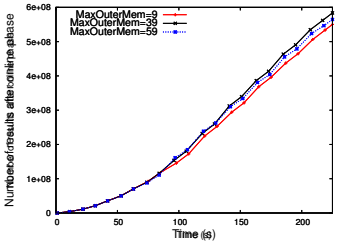

Fig. 18. Zipf distribution, varying MaxOuterMem

• DINER achieves a faster output rate in an environment of changing data rates and delays.

• DINER uses much less memory, as depicted in Table III. The reason for that is that it has a smaller "work unit" (a single inner relation block) and is able to switch over to the Arriving phase with less delay, without letting the input buffer become full.

• Finally, notice that in the first experiment of Figure 15, RPJ fails due to memory overflow. You can see in Table III that the maximum input buffer size RPJ needs in this case is $40,000$, while the available memory is $10,000$ tuples. For less available memory, HMJ fails also – the relevant experiment is omitted due to lack of space.

D. Sensitivity Analysis

In the previous sections we have already discussed its performance in the presence of smaller or larger network/source delays, and in the presence of non-stationarity in the tuple streaming process. Here we discuss DINER's performance when the available memory varies and also when the skew of the distribution varies.

Table IV refers to the experiments for real data sets shown in Figure 8, and shows the percentage of the total join result obtained by DINER during the online phase. As we can see, if enough memory is made available, (e.g., 20% of the total input size), a very large percentage of the join tuples can be produced online, but DINER manages to do a significant amount of work even with memory as little as 5% of the input size, which, for very large relation sizes, is more realistic.

We also evaluate the DINER algorithm when one relation has a smaller size than the second. In Figure 17 the value of the join attribute is zipf distributed in both relations. While one relation has a constant number of tuples (100,000), the other relation's size varies according to the values on the x-axis. The memory size is set to 10,000 tuples and the interarrival rate is exponentially distributed with $\lambda = 0.1$. DINER is a nested loop based algorithm and it shows superior performance as one relation gets smaller since it is able to keep a higher percentage of the smaller relation in memory.

We finally evaluated the sensitivity of the DINER algorithm to the selected value of the MaxOuterMem parameter, which controls the amount of memory (from the total budget) used during the Reactive phase. We varied the value of MaxOuterMem parameter from 9 to 59 blocks. The experiment, shown in Fig. 18, showed that the performance of DINER is very marginally affected by the amount of memory utilized during the Reactive phase.

V. Conclusions and Future Directions

We propose DINER, a new adaptive join algorithm for maximizing the output rate of tuples, when both relations are being streamed to our local site. The advantages of DINER stem from (i) its intuitive flushing policy that maximizes the overlap among the join attribute values between the two relations, while flushing to disk tuples that do not contribute to the result and (ii) a novel re-entrant algorithm for joining disk-resident tuples that were previously flushed to disk. Moreover, DINER can efficiently handle join predicates with range conditions, a feature unique to our technique. Through our experimental evaluation, we have demonstrated the advantages of DINER over existing algorithms in a variety of real and synthetic data sets, its resilience in the presence of varied data and network characteristics and its robustness to parameter changes.

One of the plausible characteristics of DINER is that it produces partial results early. It would thus be interesting to extend it in a way that can also provide statistical guarantees for online aggregation applications, similarly to [7], or to investigate weighted schemes for applications when it is more important to receive early partial results for specific areas of the domain. We are currently investigating these issues.

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