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Abstract Continuous query processing in data stream management systems (DSMS) has received considerable attention recently. Many applications share the same need for processing data streams in a continuous fashion. For most distributed streaming applications, the centralized processing of continuous queries over distributed data is simply not viable. This paper addresses the problem of computing approximate answers to continuous join queries over distributed data streams. We present a new method, called DHTJoin, which combines hash-based placement of tuples in a Distributed Hash Table (DHT) and dissemination of queries by exploiting the embedded trees in the underlying DHT, thereby incuring little overhead. DHTJoin also deals with join attribute value skew which may hurt load balancing and result completeness. We provide a performance evaluation of DHTJoin which shows that it can achieve significant performance gains in terms of network traffic.

Keywords Data Stream Management, · Continuous Join Queries · DHT Networks · Distributed Query Execution · Load Balancing · Result Completeness

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1 Introduction

Recent years have witnessed major research interest in Data Stream Management Systems (DSMS), which can manage continuous and unbounded sequences of data items. There are many applications that generate data streams including financial applications [7], network monitoring [34], telecommunication data management [6], sensor networks [4], etc. Processing a query over a data stream involves running the query continuously over the data stream and generating a new answer each time a new data item arrives. However, the unbounded nature of data streams makes it impossible to store the data entirely in bounded memory. This makes difficult the processing of queries that need to compare each new arriving data with past ones. For example, real data traces of IP packets from an AT&T data source [13] show an average data rate of approximately 400 Mbits/sec, which makes it hard to keep pace for a DSMS. Moreover, a DSMS may have to process hundreds of user queries over multiple data sources. For most distributed streaming applications, the naive solution of collecting all data at a single node is simply not viable [8]. Therefore, we are interested in techniques for processing continuous queries over collections of distributed data streams. This setting imposes high processing and memory requirements. However, approximate answers are often sufficient when the goal of a query is to understand trends and making decisions about measurements or utilizations patterns.

One technique for producing an approximate answer to a continuous query is to execute the query over a sliding window [14] that maintains a restricted number of recent data items. This allows queries to be executed in finite memory, in an incremental manner by generating new answers each time a new data item arrives. Moreover, in the majority of real world applications emphasizing recent data is more informative and useful than old data. Notice that a sliding window is a natural method for approximation that is part of the query semantics expressed by the user in the query. The size of a window is specified using either a time interval (time-based) or a count on the number of tuples (count-based). In this work we consider time-based windows.

In continuous query processing the join operator is one of the most important operators, which can be used to detect trends between different data streams. For example, consider a network monitoring application that needs to issue a join query over traffic traces from various links, in order to monitor the total traffic that passes through three routers (R_1, R_2 and R_3) and has the same destination host within the last 10 minutes. Data collected from the routers generate streams S_1,S_2 and S_3. The content of each stream tuple contains a packet destination, the packet size and possibly other information. This query can be posed using a declarative language such as CQL [2], a relational query language for data streams, as follows:

q_1: Select sum (S_1.size)
From S_1[range 10 min], S_2[range 10 min], S_3[range 10 min]
Where S_1.dest=S_2.dest and S_2.dest=S_3.dest

To emphasize access to recent data, the window conceptually slides over the input streams thereby giving rise to a type of join called *sliding window join*. In this paper, we address the problem of computing approximate answers to sliding window joins over data streams. Our solution involves a scalable distributed sliding window that takes advantage of the indexing power of DHT networks and can be equivalent to thousands of centralized sliding windows. We propose a method, called DHTJoin, which deals with efficient processing of join queries over all data items which are stored in the distributed sliding window. To this end, DHTJoin combines hash-based placement of tuples in the DHT and dissemination of queries. We evaluated the performance of DHTJoin through simulation. The results show the effectiveness of our solution compared with previous work.

This paper is an extended version of [28] with the following added value. First, we present a dissemination system (Section 3.1) based on the trees formed by DHT links that uses $O(n-1)$ messages. This yields an important reduction of network traffic compared with the $O(\frac{nlogn}{2})$ messages generated by the dissemination system proposed in our previous work. Considering that nodes that fail (or leave the network) during query execution may cause problems in the generation of join results and the dissemination of queries, we propose a solution to deal with node failures (Section 4). In Section 5, we show analytically that DHTJoin can scale up the processing of continuous join queries using multiple peers and improves the completeness of join results linearly as memory capacity is increased. In Section 6, we provide a new solution to handle data skew during the execution of continuous join queries. Finally, in Section 7 we report experimental results that show the effectiveness of our approach.

1.1 Contributions

In summary, we propose a novel method (DHTJoin) for the execution of continuous join queries with the following contributions:

- DHTJoin identifies, using query predicates, a subset of tuples in order to index the data required by the user's queries, thus reducing network traffic. This is more efficient than the approaches based on structured P2P overlays, e.g. PIER [16] and RJoin [17], which typically index all tuples in the network. Furthermore, our approach dynamically indexes tuples based on new attributes when new submitted queries contain differents predicates.
- We provide an analytical evaluation of the best number of nodes to obtain a certain degree of completeness given a continuous join query.
- DHTJoin tackles the dynamic behavior of DHT networks during query execution and dissemination of queries. When nodes fail during query dissemination, DHTJoin uses a gossip-based protocol that assures 100% of network coverage. When nodes fail during query execution, DHTJoin propagates messages to prevent nodes of sending intermediate results that do not contribute to join results, thereby reducing network traffic.

Table 1: Symbols used in this paper

Symbol	**Description**
n	number of nodes
m	number of streams
$S = \{S_1, S_2, ..., S_m\}$	set of streams
A^i_j	j-th attribute of stream S_i
λ_i	arrival rate of stream S_i in tuples/sec
$S[W_i]$	sliding window of stream S_i
W_i	window size of $S[W_i]$ in seconds
$Q = \{Q_1, Q_2, ..., Q_n\}$	set of queries
$\mathcal{P}$	set of equijoin predicates of a query Q_i
$QP = \{QP_1, QP_2, ..., QP_n\}$	set of query plans
sel	join selectivity $\in$ [0..1]
$m(S_i)$	function that returns the memory assigned to S_i tuples

– DHTJoin provides an efficient solution to deal with overloaded nodes as a result of data skew. The key idea is to distribute the tuples of an overloaded node to some underloaded nodes, called *partners*. When a node gets overloaded, DHTJoin discovers partners using information in the routing table and determines what tuples to send them using the concept of domain partitioning. We show that, in this case, DHTJoin incurs only one additional message per joined tuple produced, thus keeping response time low.

1.2 Organization

The rest of this paper is organized as follows. In Section 2, we introduce our system model and define the problem. In Section 3, we describe DHTJoin. In Section 4, we discuss how DHTJoin deals with node failures. In Section 5, we provide an analysis of result completeness of our algorithms which relates memory constraints, stream arrival rates and result completeness. In Section 6, we describe how DHTJoin deals with data skew. In Section 7, we provide a performance evaluation of our solution through simulation using Java. In Section 8, we discuss related work. Section 9 concludes.

2 System Model and Problem Definition

In this section, we introduce a general system model for processing data streams over DHTs, with a DHT and data model, and a stream processing model. Then, we state the problem. For readability, Table 1 summarizes the main symbols used in this paper.

2.1 DHT and Data Model

In our system, the nodes of the overlay network are organized using a DHT protocol. While there are significant implementation differences between DHTs [30][33], they all map a given key k onto a node p using a hash function and can lookup p efficiently, usually in $O(logn)$ routing hops where n is the number of nodes. DHTs typically provide two basic operations : *put(k, data)* stores a key k and its associated *data* in the DHT using some hash function; *get(k)* retrieves the data associated with k in the DHT. In a DHT each node has a identifier denoted by $node_{id}$. Nodes insert data in the form of relational tuples and queries are represented in a relational query language for data streams such as CQL [2]. Tuples belonging to the same stream are inserted by the same node and continuous queries are originated at any node of the network. Tuples and queries are timestamped to represent the time that they are inserted in the network by some node. We assume that data and query sources are equipped with well-synchronized clocks by using the public domain Network Time Protocol (NTP) designed to work over packet-switched and variable latency data networks and already tested in distributed DSMS [35]. Each tuple has a unique key generated using the name of the node that inserts it, the name of the relation to which it belongs and its timestamp. Additionally, each query is associated with a unique key q_{id} used to identify it in query processing, optimization tasks and to relate it to the node that submitted it.

Let us now formally define continuous join queries and the type of continuous queries that we consider in our approach. Let $S = \{S_1, S_2, ..., S_m\}$ be a set of data streams. Each data stream S_i has a relational schema $(A_1^i, A_2^i, ..., A_{n_i}^i)$, where each A_j^i is an attribute. We use equijoin and conjunctive predicates, i.e., the *where* clause uses exclusively conjunctions of atomic equality conditions. Let $Q_i = (S', \mathcal{P})$ be a continuous join query defined over $S' \subseteq S$ and composed by $\mathcal{P}$ that represents a set of equijoin predicates. As in [43][17], we identify two types of join queries depending on the attributes involved in $\mathcal{P}$. A query of type 1 is a join query with a set of equijoin predicates as following: $\mathcal{P} = \{(S_1.A_k^1 = S_2.A_k^2), (S_2.A_k^2 = S_3.A_k^3), ..., (S_{m-1}.A_k^{m-1} = S_m.A_k^m)\}$, i.e., the join attribute is the same in all the relations of the query (e.g. query q_1 of Sect. 1). A query of type 2 is a join query with a set of equijoin predicates as following: $\mathcal{P} = \{(S_1.A_k^1 = S_2.A_k^2), (S_2.A_l^2 = S_3.A_l^3), (S_3.A_m^3 = S_4.A_m^4), ..., (S_{m-1}.A_{n_m}^{m-1} = S_m.A_{n_m}^m)\}$, i.e., the join attributes are different and adjacent joins must have a common relation.

2.2 Stream Processing Model

A data stream S_i is a sequence of tuples ordered by an increasing timestamp where $i \in [1..m]$ and $m \geq 2$ denotes the number of input streams. At each time unit, a number of tuples of average size l_i arrives to stream S_i. We use λ_i to denote the average arrival rate of a stream S_i in terms of tuples per second.

Many applications are interested in making decisions over recently observed tuples of the streams. This is why we maintain each tuple only for a limited time. This leads to a sliding window $S[W_i]$ over S_i that is defined as follows. Let W_i denotes the size of $S[W_i]$ in terms of seconds, i.e. the maximum time that a tuple is maintained in $S[W_i]$. Let $TS(s)$ be a function that denotes the arrival time of a tuple s and t be current time. Then $S[W_i]$ is defined as $S[W_i] = \{s|s \in S_i \wedge (t - TS(s) \leq W_i\}$. Tuples continuously arrive at each instant and expire after W_i time steps (time units). Thus, the tuples under consideration change over time as new tuples get added and old tuples get deleted. In practice, when arrival rates are high, the window sizes are long and the memory dedicated to the sliding window is limited, it becomes full rapidly and many tuples must be dropped before they naturally expire . In this case, we need to decide whether to admit or discard the arriving tuples and if admitted, which of the existing tuples to discard. This kind of decision is made using a load shedding strategy [32][36] which yields that only a fraction of the complete result will be produced.

2.3 Problem Definition

In this paper, we address the problem of processing join queries over data streams. We view a data stream as a sequence of tuples ordered by monotonically increasing timestamps. The nodes are assumed to synchronize their clocks using the public domain Network Time Protocol (NTP),thus achieving accuracies within milliseconds [3]. Each tuple and query have a timestamp that may be either implicit, i.e. generated by the system at arrival time, or explicit, i.e. inserted by the source at creation time.

This paper focuses on query execution (not query optimization). Thus, we assume the existence of a query optimizer that translates a query represented in CQL [2] into a query plan in the form of an operator tree. Since an MJoin operator [37] is used by default to specify join operations, only the join order needs to be specified by the optimizer, i.e. the choice of how to execute MJoin operators (e.g. which nodes) is done at runtime using our method. Each query Q_i has a query plan QP_i that specifies the ordering of the join operations.

Formally, the problem can be defined as follows. Let $S = \{S_1, S_2, ..., S_m\}$ be a set of data streams, and $QP = \{QP_1, QP_2, ..., QP_n\}$ be a set of query plans of the following set of continuous join queries $Q = \{Q_1, Q_2, ..., Q_n\}$, where $Q_i = (S', \mathcal{P})$ is a continuous join query defined over $S' \subseteq S$ and $\mathcal{P}$ represents a set of equijoin predicates. Our goal is to provide an efficient method to execute QP over S in terms of network traffic.

3 DHTJoin Method

In this section, we describe our solution, DHTJoin, for processing continuous join query processing using DHTs. The main issues for processing continuous

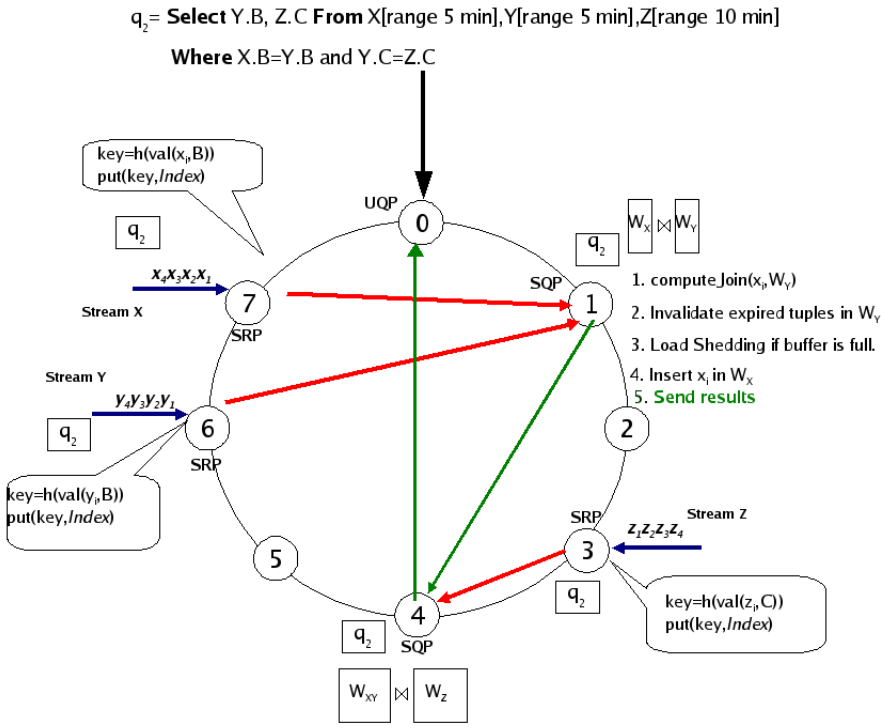


Fig. 1: A DHTJoin example using a query of type 2

queries in DHTs are the following: how to route data and queries to nodes in an efficient way; how to provide a data storage mechanism for storing relational data; and how to provide a good approximate answer to join queries.

DHTJoin has two steps: dissemination of queries and indexing of tuples. A query is disseminated using the embedded tree inherents to DHTs networks and a tuple inserted by a node is indexed, i.e., stored at another node using DHT primitives. However, a node indexes a tuple only if there is a query that contains an attribute of the arriving tuple in $\mathcal{P}$. To this end, a node stores locally a disseminated query and once it receives a tuple it checks for already disseminated queries that contain an attribute of the arriving tuple in $\mathcal{P}$.

We describe the design of DHTJoin based on Chord which is a simple and very popular DHT. However, the techniques used here can be adaptable to others DHTs such as Pastry [31] and Tapestry [41].

To process a query, we consider different kinds of nodes. The first kind is Stream Reception Peers (SRP) for indexing tuples to the second kind of nodes, the Stream Query Peers (SQP). In Figure 1, nodes 3, 6 and 7 correspond to SRP because they receive tuples belonging to streams z, y, and x respectively. SQP are responsible for executing query predicates over the arriving tuples using their local sliding windows, and sending the results to the third kind of

node(s), the User Query Peers (UQP). In Figure 1, nodes 1 and 4 are SQP because node 1 computes the join predicate $X.B = Y.B$ of query q_2 (submitted at node 0) and node 4 performs the join predicate $Y.C = Z.C$ of q_2. In addition, node 0 is a UQP because query q_2 was submitted at this node.

To support dissemination of queries, a node must be a dissemination node (i.e. executes a dissemination protocol) while to index tuples, a node must be a DHT peer. Note that the difference between SRP, SQP and UQP is functional and the same node can support all these functionalities.

3.1 Disseminating Queries

Each new query issued by users should be disseminated to all nodes because by using S' and the set of predicates $\mathcal{P}$ of a query a node decide which tuples and attributes should be indexed. The query dissemination system consists of a set of DHT nodes. A query can originate at any of the nodes and is disseminated using a tree [5].

To disseminate a query, DHTJoin dynamically builds a dissemination tree as proposed in [11]. The basic idea is to consider that in a DHT as Chord a *lookup* operation can be perceived as a binary search [11] that generates a binary tree using the nodes (links) stored in the routing table. The root of the tree is the node that submits the query (an UQP node). The query is disseminated from the root node to all nodes of the DHT using a divide-and-conquer approach. When a node receives a disseminated query, it is stored locally in a *query table* (QT), thus allowing to know what is the attribute of an arriving tuple that must be used in the indexing process. This is important since a tuple s_i is indexed using an attribute A^i_j only if it is contained in the set $\mathcal{P}$ allowing to decrease network traffic and providing a better utilization of local SQP resources by avoiding the indexing of tuples using an attribute that is not being involved in a query.

To disseminate a query, an UQP node creates a dissemination message $Dmsg = (node_{id}, q_{id}, Q_i, QP_i, ts, \mathcal{R})$ containing its own node identifier $node_{id}$, an unique query identifier q_{id}, the query $Q_i = (S', \mathcal{P})$, the query plan QP_i, a timestamp ts that denotes the arrival time of Q_i and a range of dissemination $\mathcal{R}$. A node that receives a $Dmsg$ store the query in its QT and creates a new $Dmsg$ preserving the $node_{id}$, the q_{id}, the timestamp ts, the query Q_i and the query plan QP_i, and changing $\mathcal{R}$. For example, using a fully-populated Chord ring with 8 nodes, each one contains a routing table of $log(n)$ entries called fingers. The i^{th} entry in the table at node n contains the identity of the first node that succeeds or equal $n+2^i$. A dissemination message initiated at node 0 is sent to finger nodes 1, 2 and 4 (see Figure **??**) giving them the disseminations limits [1,2), [2,4) and [4,0) respectively. The disseminations limits are used to restrict the forwarding space of a node and they are constructed using as a upper bound the finger $i + 1$. Each node applies the same principle reducing the search scope. When node 2 receives the dissemination message with limits [2,4) it examines the routing table and sends the message to node 3. Once

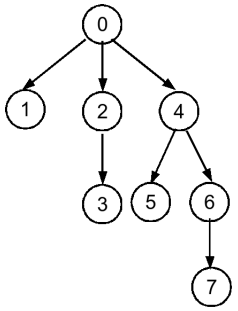


Fig. 2: A dissemination tree formed using DHT links of a 8-node Chord ring

node 4 receives the dissemination message it examines the routing table and sends the message to nodes 5 and 6 with limits [5,6) and [6,0) respectively. In the same way, node 5 does not continues with the dissemination process (since there are no nodes between [5,6)) and node 6 disseminates the message to node 7. This forwarding process generates $n-1$ messages and a tree of depth $log(n)$, which fixes the latency of query dissemination.

3.2 Indexing Tuples

The indexing of tuples allows DHTJoin to distribute the query workload across multiple DHT nodes. Let us describe how DHTJoin indexes tuples for streams $S = \{S_1, S_2, ..., S_m\}$. Let s_i be a tuple belonging to S_i. Let $A = (A_1^i, A_2^i, ..., A_{n_i}^i)$ be the set of attributes in s_i and $val(s_i, A_j^i)$ be a function that returns the value of the attribute $A_j^i \in A$ in tuple s_i. Let h be a uniform hash function that hashes $val(s_i, A_j^i)$ into a DHT key, i.e. a number which can be mapped to a $node_{id}$. A node that index a tuple $s_i \in S_i$ creates a message $Index = (S_i, s_i, A_j^i, ts)$ containing the stream S_i which the tuple belongs to, the tuple s_i being indexed, the attribute used to index the tuple and a timestamp ts that denotes the arrival time of the tuple. Let $S[W_i]$ denote a sliding window on stream S_i. Recall that we use time-based sliding windows where W_i is the size of the window in time units. At time t, a tuple s_i belongs to $S[W_i]$ if it has arrived in the time interval $[t - W_i, t]$.

For indexing a tuple s_i that arrives at an SRP, each tuple obtains an index key computed as $key = h(val(s_i, A_j^i))$. The attribute A_j^i in s_i is chosen by searching locally in the QT for queries that contains A_j^i in $\mathcal{P}$. Then to index s_i the SRP node creates a $Index$ message and sends it to a SQP (the node responsible for key in the DHT), by performing $put(key, Index)$. Thus, tuples of different streams having the same key are put in the same SQP node and are stored in sliding windows where they are processed to produce the result of a specific join predicate.

3.3 Query Execution

Query processing in a DSMS entails the generation and execution of a query plan. This paper focuses on the execution part. For simplicity, we assume that the query plan is an operator tree that specifies the ordering of operations (i.e. join order) and it is included in the *Dmsg* message of the query dissemination step (see Section 3.1).

Queries of type 1 are executed using partitioned parallelism with SQP nodes implementing the MJoin operator [37]. A query plan contains an operator tree for each stream present in the query (see Figure 3) that could be optimized locally, thus generating a new operator tree. Each node in the operator tree represents a join operator and an edge represents the next stream to probe. Queries of type 2 are executed using pipelined parallelism (see Figure 5). For queries of type 2, the query plan is assumed to be generated by a centralized query optimizer based on a cost model which captures information regarding data (e.g. tuples' arrival rates) and operators (e.g. cost of a join) [43]. Each node in the operator tree represents a join operator implemented using MJoin and an edge represents the next step in the pipeline.

In this section, we describe the execution of queries of type 1 and 2 in DHTJoin.

3.3.1 Queries of Type 1

In this type of queries, DHTJoin uses partitioned parallelism [23] where different nodes execute independently the same query plan on different data partitions. By default, DHTJoin instantiates an MJoin operator [37] for queries of type 1. Mjoin considers n inputs streams symmetrically and allows the tuples from the streams to arrive in an arbitrary interleaved fashion. The basic algorithm of MJoin creates as many hash tables (states) as there are join attributes in the query. When a new tuple from a stream arrives into the system, it is probed with the other $n-1$ streams in some order to find the matches for the tuple. The order in which the streams are probed is called the *probing sequence*. Figure 3 shows an MJoin operator for a 3-way continous join query expressed using CQL [2]. There are three hash tables corresponding to the three join attributes of the query and three probing sequ ences. An MJoin operator is ready to accept a new tuple on any input stream at any time. Upon arrival, the new tuple is used to probe the remaining hash tables, thus generating a result as soon as possible. MJoin implements a lightweight tuple router that, considering the *probing sequence*, routes the arriving tuples to the remaining hash tables. The following steps are executed when a new tuple $x \in X$ arrives:

- x is inserted into the X hash table.
- The *probing sequence* for an X tuple is $Y \rightarrow Z$ (see Figure 3).
- x is used to probe the hash table on Y to find the tuples that satisfy the join predicate $X.dest = Y.dest$. Intermediate tuples are generated by concatenating x with the matching tuples $y_i \in Y$, if any.

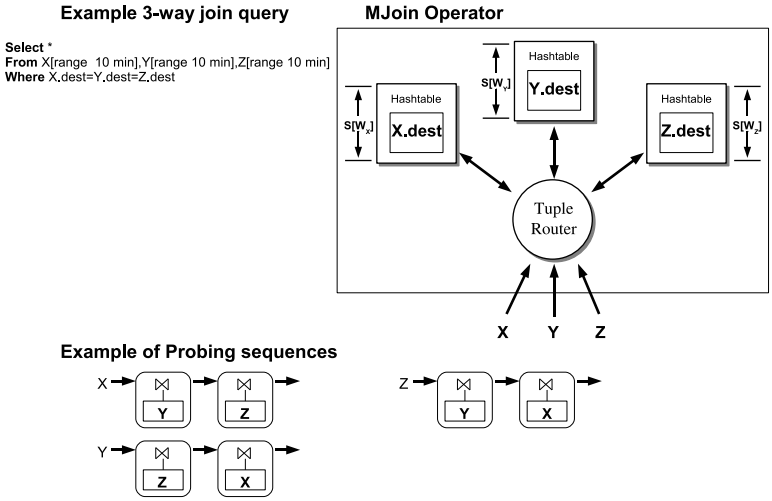


Fig. 3: MJoin operator for a 3-way join query of type 1

– If any result tuples were generated, they are routed to the Z hash table in order to find the tuples that satisfy the join predicate $Y.dest = Z.dest$.

MJoin integrates sliding windows as follows. Let us consider the MJoin operator of Figure 3. Each hash table stores the tuples that fall within the current window period which, in the case of q_1,correspond to 10 minutes for the streams X, Y and Z. For example, for each arriving tuple $x \in X$, before probing the hash table on Y, the Y tuples that are outside of the window $S[W_Y]$ are eliminated. If an intermediate result tuple xy_i is generated, the Z tuples that are outside of the window $S[W_Z]$ are eliminated before the probe step.

Choosing a *probing sequence* is very important in MJoin because it must ensure that the smallest number of intermediate results is generated. This process is supported by heuristic-based ordering algorithms [14][37]. MJoin is very attractive when processing continuous queries over data streams because the query plans can be changed by simply changing the *probing sequence*. Thus, each SQP node that processes a query of type 1 can optimize the execution plan of the query independently.

Let us illustrate how DHTJoin perfoms query processing with the following query of type 1:

q_1: Select sum (X.size)
From X[range 10 min], Y[range 10 min], Z[range 10 min]
Where $X.dest = Y.dest = Z.dest$

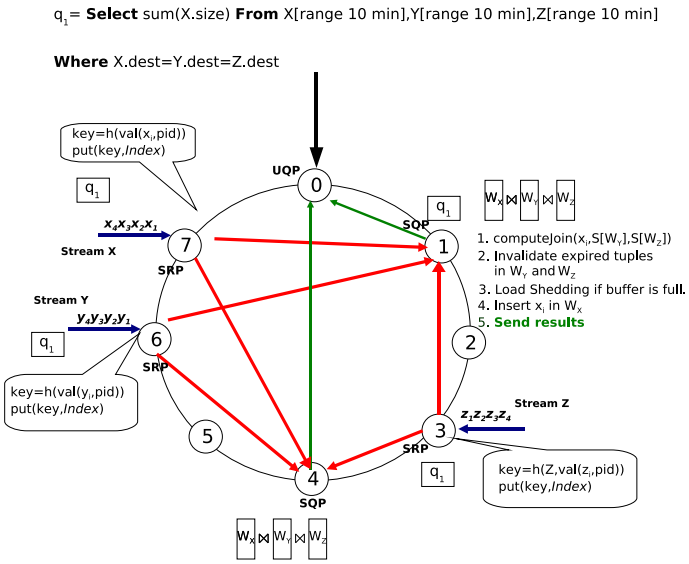


Fig. 4: Execution of a query of type 1 in DHTJoin

Query q_1 is submitted at node 0 and disseminated, using the strategy proposed in Section 3.1, over the entire network as soon as it is submitted. SRP nodes 7, 6 and 3 index x_i, y_i and z_i tuples and check locally in their QT whether q_1 contains in $\mathcal{P}$ an attribute belonging to the arriving tuples. Recall that in a query of type 1, the join attribute is the same in all relations, so that all the tuples having the same attribute value are located in the same SQP node without producing intermediate results. Therefore, q_1 can be executed independently at different SQP nodes, each using an MJoin operator. In our example, SQP nodes 1 and 4 process q_1 on different partitions of X, Y and Z streams using an MJoin operator (see Figure 4). The results produced by SQP nodes 1 and 4 are sent directly to the UQP node (whose address was provided in the $Dmsg$ m essage when q_1 was disseminated).

3.3.2 Queries of Type 2

DHTJoin executes queries of type 2 using pipelined parallelism [23] where different nodes run in a pipelined fashion such that tuples output by a node can be fed to another node as they get produced. Recall that DHTJoin partitions the streams by hash functions. For example, let us consider query q_2 with the following set of predicates $\{(X.B = Y.B), (Y.C = Z.C)\}$. Streams X and Y are indexed based on the value of attribute B while stream Z is indexed based on the value of attribute C which is placed at a node different from where

the stream Y is indexed. Therefore, redirection of intermediate join results is necessary in this type of query. Another solution is to index the stream Y twice, i.e. based on attributes B and C executing $X \bowtie_B Y$ and $Y \bowtie_C Z$ in parallel. However, we do not consider this solution for the two following reasons:

- It duplicates unnecessarily the indexing of Y tuples.
- It introduces more messages and processing costs because the output tuples of the two joins must be processed to find the final join result.

For queries of type 2, we assume that the query optimizer generates a query plan based on a bushy tree of binary joins that has the potential of executing independents subtrees concurrently. Local operators are executed using an MJoin operator and can be optimized as for queries of type 1.

Let us illustrate how DHTJoin perfoms query processing using the following query of type 2:

q_2: Select Y.B, Z.C
From X[range 5 min], Y[range 5 min], Z[range 5 min]
Where X.B=Y.B and Y.C=Z.C

This query specifies an equijoin among X, Y and Z streams over the last 5 minutes. Query q_2 is submitted at node 0 and disseminated over the entire network as soon as it is submitted. Thus, after a while, all nodes know the existence of this query and are able to index the incoming streams (tuples). We assume that the query plan generated for q_2 is $(X \bowtie_B Y) \bowtie_C Z)$. Once an X-, Y- or Z-tuple arrives at nodes 7, 6 and 3 respectively, each node checks locally in its QT whether the query q_2 contains in $\mathcal{P}$ an attribute belonging to the arriving tuple (see Figure 1). If so, nodes 7, 6 and 3 execute the task of an SRP. For instance, in our example, node 7 indexes x_i because the attribute $B \in X$ is in the set $\mathcal{P}$ of q_2. Node 7 creates a message $Index = (X, x_i, B, ts)$, generates an index key using $key = h(val(x_i, B))$ and indexes the tupl e using $put(key, Index)$. The equijoin predicate $X.B = Y.B$ belonging to q_2 is evaluated at a SQP (node 1) only with tuples that arrive in the system after the query.

Sliding windows are used at each SQP node, as for queries of type 1, as follows. For example, at node 1 in Figure 1, tuples expired in $S[W_Y]$ are invalidated upon the arrival of X-tuples. The load shedding procedure is executed over $S[W_X]$'s buffer if there is not enough memory space to insert the arriving tuple.

The SQP node 1 searches in the query plan of q_2 what is the next step to follow and concludes that the intermediate results $x_i y_j$ must be sent to another node using the value of C attribute belonging to the Y-tuple. Thus the SQP node 1 creates a message $Index = (XY, x_i y_j, C, max(TS(x_i), TS(y_j)))$, generates an index key using $key = h(val(y_j, C))$ and index the intermediate tuple using $put(key, Index)$ to SQP node 4. The join result tuples produced

by SQP node 4 are immediately sent to the appropriate UQP node (whose address is provided when starting query dissemination).

3.4 DHTJoin on Other DHTs

The design of DHTJoin is based on Chord which is a simple and very popular DHT. However, the dissemination technique and the indexing of tuples used can be adapted to others DHTs such as Pastry [31] and Tapestry [41]. In the dissemination of queries, recall that the basic idea (using Chord) is to consider a *lookup* operation as a binary search in spite of its ring geometry. The routing algorithms in Pastry and Tapestry are both similar in spirit to the PRR's routing algorithm [29] which is based on a tree hierarchical organization. This makes of Pastry and Tapestry a good choice to implement the query dissemination.

We consider Pastry as an example and demonstrate how to apply query dissemination using the mechanism proposed in [5]. In Pastry each node has a unique *nodeId* assigned from a identifier space of 128 bits. Application-specific objects are assigned unique identifiers called keys from the same identifier space. Assuming a network of size n, each Pastry node maintains a routing table of $log_{2^b} n$ rows with 2^b entries each. For the purpose of routing, the *nodeId* and keys can be thought of as a sequence of L digits in base 2^b. The mechanism to route a message is prefix-based, i.e. the routing is achieved by forwarding the message to a node that shares a common prefix by at least one more digit. Pastry can route a message to any node in $log_{2^b} n$ hops. For ease of explanation, we use $b = 1$, $L = 3$ and a network of 8 nodes. A dissemination message initated a node 000 contains the query id q_{id} and the message is sent to the 3 nodes of its routing table 100, 010 and 001 adding the routing table row r of each node. When a node receives a dissemination message, it searches in the routing table all the nodes located in rows greater than r (if any) and disseminates the message to them. This process is repeated at each node that receives the message, thus generating a dissemination tree of depth $log(n)$.

Regarding the indexing of tuples, we use primitives which represent capabilities that are common to all DHTs. DHTs typically provide two basic operations [9]: *put(k, data)* stores a key k and its associated *data* in the DHT using some hash function; *get(k)* retrieves the data associated with k in the DHT. Thus, we can process continuous join queries in other DHTs.

4 Dealing with Node Failures

In this section, we discuss how DHTJoin deals with node failures during query execution. By node failure, we mean various situations by which a DHT node stops participating in query execution (e.g. because it crashes). We address this issue considering two situations: (1) *Failure of a node during query dissemination.* Recall that the dissemination of queries allows to decrease network

traffic by avoiding the indexing of tuples using an attribute that is not being involved in a query. However, its benefits can be lost when the tree hierarchical organization of the dissemination is broken due to node failures. (2) *Failure of a node during query execution.* The failure of a node stops the indexing of tuples. With queries of type 2, this situation can generate partial results that never contribute to generate join results.

4.1 Failures during Query Dissemination

In DHTJoin, continous join queries are originated at any node of the DHT and disseminated using a tree. The dissemination of queries achieves a network coverage of 100%, takes $O(logn)$ hops to reach every node in the network and generates $n-1$ messages. However, dynamic changes of the structure of the DHT network can disturb the dissemination. The failure of a node in the tree structure generated by the dissemination makes the entire subtree under this node unreachable. To provide realibility in the dissemination of queries, we propose to use a gossip based protocol as a complementary to our tree based dissemination.

Basically, gossip proceeds as follows: a node n_i knows a group of other nodes or *contacts*, which are maintained in a list called $n_i's$ *view*. Periodically $node_i$ selects a contact $node_j$ from its view to gossip: $node_i$ sends its information to $node_j$ and receives back other information from $node_j$.

We integrate gossip to DHTJoin's dissemination procedure as follows. The *view* maintained by the nodes is the neighbor list present in DHTs. All nodes that receive a disseminated query forward periodically the query to a randomly chosen neighbor. To this end, a node creates a gossip message $Gmsg$ and executes $send(receiver, Gmsg)$ where $receiver$ is the destination node of message $Gmsg$.

Our algorithm to gossip query dissemination messages proceeds as follows. A message $Gmsg$ is generated at any node that has already received a user-level query Q_i. A message $Gmsg = (Q_i, q_{id}, QP_i, TS(Q_i), L_d)$ contains a query Q_i, a unique query identifier q_{id}, a query plan QP_i, a timestamp $TS(Q_i)$ and a partial dissemination list L_d composed by the nodes of its local *view* to which the message has been sent (not necessarily received by all nodes of L_d due to the dynamic nature of the network) and the node that sent the message to it. To process a gossip message, a node that receives a message $Gmsg = (Q_i, q_{id}, QP_i, TS(Q_i), L_d)$ chooses a random node n_r from its *view* and forwards the message $(Q_i, q_{id}, QP_i, TS(Q_i), L_d \cup n_r)$ to n_r only if it has not been already chosen in previous gossip rounds.

4.2 Failures during Query Execution

DHTJoin distributes the query workload across multiple DHT nodes and provides a mechanism that avoids indexing tuples using attributes not contained

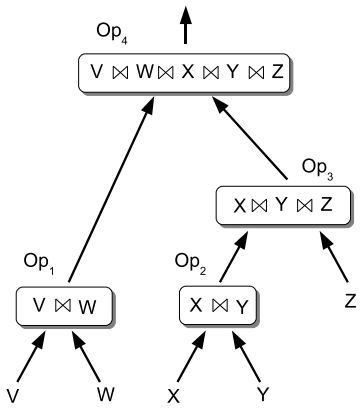


Fig. 5: Query Plan of a 5-way continuous join query of type 2

in the set $\mathcal{P}$ of a query. However, when a node fails, another node can generate partial results irrespective of whether they produce join query results. In this section, we address the problem of indexing partial results that never contribute to generate join results.

For example, let us consider the following query plan $(V \bowtie W) \bowtie ((X \bowtie Y) \bowtie Z)$ for a query of type 2 where there are nodes connected by a producer-consumer relationship, whereby a producer node generates tuples to be processed by a consumer node [40]. The query plan (see Figure 5) shows the relations between producers and consumers. We assume that a join operator Op_i resides at node n_i. Operator Op_3 is a producer of $X \bowtie Y \bowtie Z$ tuples for Op_4 and a consumer w.r.t Op_2 and SRP of stream Z. Recall that in a query of type 2, the operators are placed at different SQP nodes and the query plan is provided in the query dissemination step. If the node n_1 fails, the indexing of $V \bowtie W$ intermediate result tuples is stopped, thus yielding no join results because of no matching tuples in node n_4. Furthermore, if no matching tuple of $V \bowtie W$ appears at node n_4 before expiration of $X \bowtie Y \bowtie Z$ tuples, the resources involved in sending, processing and storing these tuples are wasted.

To address this problem, we propose the following solution. If node n_4, where Op_4 is executed, detects that $V \bowtie W$ tuples are not being generated by node n_1 it sends a message to node n_3 to alert that it is not necessary to send $X \bowtie Y \bowtie Z$ tuples. Consequently, as the demand of Op_3 as a consumer has changed, it propagates the alerting message to node n_2 and to the SRP of stream Z only if there does not exist another query that needs $X \bowtie Y \bowtie Z$ tuples generated by Op_3. This condition is verified at all the operators that receive an alerting message. Once the communication with n_1 is established again, node n_4 sends a resume message to n_3 in order to continue with the production of tuples and node n_3 propagates the resume message it proceeds. If in a query plan, a consumer also acts as a producer, it is not necessary to alert

its consumer. The reason is that a consumer is always testing its producers in the query plan in order to detect a problem. Therefore, the consumer that detects that there are tuples not being generated by a producer must trigger an alert message only to the other producers (the descendents) in the query plan if any. Procedure 1 describes the behaviour of the consumer that trigger the alert message to the producers of the query plan. Procedure 2 describes the behaviour of a producer in order to handle and alert message.

Procedure 1 Send_AlertMSG(q)

Input: the query q
1: **for** all the descendents $\in$ query plan of q **do**
2: $alertMSG \leftarrow \{q, \{suspend|resume\}\}$
3: send(myID,alertMSG)
4: **end for**

In Procedure 1, a consumer sends an alert message to all the other producers of the query plan of query q. The consumer sends a suspend message when it detects that there are tuples not being generated by a producer. Otherwise, it sends a resume message.

Procedure 2 Handle_AlertMSG(consumerID, alertMSG)

Input: consumerID, the identifier of the consumer node in the Chord ring. **alertMSG** is a message containing the identification of the query q and the type of action {suspend,resume}
1: **if** notExists($q_i \in$ QT $\neq q$) **then**
2: propagate_AlertMSG(myID, alertMSG);
3: **end if**
4: **if** (action is suspend) **then**
5: suspend(q)
6: **else**
7: resume(q)
8: **end if**

In Procedure 2, Line 1 verifies that there does not exist another query in QT that needs the tuples generated by the producer that receives the message. If so, the producer acting as a consumer sends the message to its descendents (Line 2) in the query plan of q. Finally, the producer performs appropiate operations to suspend (Line 5) or reactivate (Line 7) locally the production of tuples related to q. By eliminating unnecessary intermediate results, this optimization yields an important reduction of network traffic and a better utilization of local resources.

5 Analysis of Result Completeness

The notion of result completeness is important in distributed and P2P databases since partial (incomplete) query answers are often only possible [26][19]. Result

completeness is thus defined as the fraction of results actually produced over the total results (which could be produced under perfect conditions). In data streaming applications, the potential high arrival rates of streams impose high processsing and memory requirements. However, approximate answers are often sufficient when the goal of a query is to understand trends and making decisions about measurement or utilization patterns. Query approximation can be done by limiting the size of states maintained for queries [18]. In our analysis we focus in the case where the memory allocated to maintain the state of a query is not sufficient to keep the window size entirely, thus reducing the received join results and completeness. DHTJoin provides more memory to store tuples, but we consider that determining the number of computing resources necessaries to achieve a certain degree of completeness for a given query is an important aspect in the setup phase of DHTJoin.

In this section, we propose formulas which relate peer memory constraints, stream arrival rates, and result completeness. We will use these formulas in our performance evaluation and they could be useful to a DHTJoin user (e.g. an application developer) to define and tune a DHT network for specific application requirements. We provide the necessary equations to calculate the completeness in a 2-way join and afterwards we generalize our results for a m-way join.

For ease of analysis, we make simplifying assumptions: the tuples are uniformily distributed across the DHT network; the memory assigned to store tuples is the same at each peer; we use the average rate to characterize the rate of arrivals of incoming tuples and stream tuples arrive in monotonically increasing order of their timestamps. We use the notations specified in Table 1. In order to illustrate our analysis, let us consider the following join query over two streams S_1 and S_2:

Q: Select *
from S_1[range 5 min], S_2[range 5 min]
where $S_1.x = S_2.x$

The expected tuple arrival rate of streams S_1 and S_2 at each node of the DHT is $\frac{\lambda_1}{n}$ and $\frac{\lambda_2}{n}$ respectively. Thus, the expected number of join tuples generated by S_1 and S_2 over sliding windows at each node can be estimated as

$$T(S_1, S_2) = sel \times (\frac{W_1\lambda_1}{n}) \times (\frac{W_2\lambda_2}{n}) \tag{1}$$

Each node needs a memory space for storing tuples in its local sliding window equivalent to $\frac{W_1\lambda_1}{n}$ and $\frac{W_2\lambda_2}{n}$. In general, if $(\frac{W_i\lambda_i}{n} > m(S_i))$ we have a loss rate (Lr) to store tuples equivalent to:

$$Lr(S_i) = \begin{cases} 0, & \frac{W_i\lambda_i}{n} \leq m(S_i) \\ \frac{W_i\lambda_i}{n} - m(S_i), & otherwise \end{cases} \tag{2}$$

Assuming that memory is insufficient to retain all the tuples in W_1 and W_2, the loss of join tuples L of S_1 and S_2 is:

$$L(S_1) = sel \times Lr(S_1) \times (\frac{W_2\lambda_2}{n}) \tag{3}$$

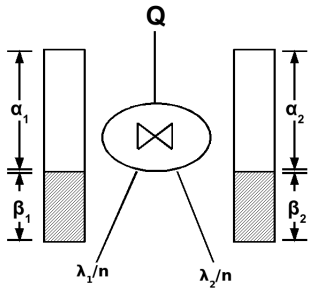


Fig. 6: A join state including stored and non stored tuples

$$L(S_2) = sel \times Lr(S_2) \times (\frac{W_1\lambda_1}{n}) \tag{4}$$

Let α_i be the S_i-tuples stored in the memory space $m(S_i)$ and β_i be the S_i-tuples not stored due to memory constraints (see Figure 6). We can rewrite equations (3) and (4) as:

$$L(S_1) = sel \times \beta_1 \times (\alpha_2 + \beta_2) = (sel \times \alpha_2 \times \beta_1) + (sel \times \beta_1 \times \beta_2)$$

$$L(S_2) = sel \times \beta_2 \times (\alpha_1 + \beta_1) = (sel \times \alpha_1 \times \beta_2) + (sel \times \beta_1 \times \beta_2)$$

Notice that the tuples related to expression $(sel \times \beta_1 \times \beta_2)$ are counted in both $L(S_1)$ and $L(S_2)$. This expression can be rewriten as: $(sel \times Lr(S_1) \times Lr(S_2))$. The total loss of join tuples TL of $S_1 \bowtie S_2$ is the sum of the loss of join tuples $L(S_1)$ and $L(S_2)$ minus the tuples counted twice:

$$TL(S_1, S_2) = L(S_1) + L(S_2) - (sel \times Lr(S_1) \times Lr(S_2)) \tag{5}$$

The completeness C of a $S_1 \bowtie S_2$ join query is the fraction of total results $T(S_1, S_2)$ minus the loss of tuples $TL(S_1, S_2)$ and total results $T(S_1, S_2)$, using equation (1) and equation (5) C is:

$$C = \frac{T(S_1, S_2) - TL(S_1, S_2)}{T(S_1, S_2)} \tag{6}$$

Developing expressions in (6) allows us to simplify C to:

$$C = \frac{n^2 \times m(S_1) \times m(S_2)}{W_1\lambda_1 \times W_2\lambda_2} \tag{7}$$

Moreover, we can write (7) as:

$$n = \sqrt{\frac{C \times (W_1\lambda_1) \times (W_2\lambda_2)}{m(S_1) \times m(S_2)}} \tag{8}$$

This equation allow us to evaluate how many peers are necessary to process a 2-way join query.

Now we generalize our analysis to m-way joins as following. Recall that the total loss of join tuples TL is the sum of the loss of join tuples minus the tuples counted more than one time. The sum of the loss of join tuples can be easily extended to an m-way join as $\sum_{i=1}^{m} L(S_i)$. However, the expression that represents the tuples counted more than one time is more difficult to generalize. We use the same method of rewriting (3) and (4) to find the expression that represents the case of tuples counted more than one time. Thus in a $S_1 \bowtie S_2 \bowtie S_3$ join we rewrite $L(S_1)$,$L(S_2)$ and $L(S_3)$, discovering that $(sel^2 \times \beta_1 \times \beta_2 \times \alpha_3)$, $(sel^2 \times \beta_1 \times \beta_3 \times \alpha_2)$ and $(sel^2 \times \beta_2 \times \beta_3 \times \alpha_1)$ are counted twice and $(sel^2 \times \beta_1 \times \beta_2 \times \beta_3)$ is counted t riple. Rewriting α_i and β_i we arrive at the following expression: $sel^2 Lr(S_1)Lr(S_2)m(S_3) + sel^2 Lr(S_1)Lr(S_3)m(S_2) + sel^2 Lr(S_2)Lr(S_3)m(S_1) + 2sel^2 Lr(S_1)Lr(S_2)Lr(S_3)$.

Repeating the same method with m-way joins ($m \geq 4$) and analyzing the resulting expressions, we arrive at the following general expression for a $S_1 \bowtie S_2 \bowtie .... \bowtie S_m$ join:

$$\sum_{k=2}^{m} \sum_{\substack{S' \subseteq S \\ |S'|=k}} \sum_{\substack{S'' \subseteq S \\ |S''|=m-k \\ S'' \cap S' = \emptyset}} (sel^{m-1}(k-1) \prod_{a \in S'} Lr(a) \prod_{b \in S''} m(b))$$

Now, the general case of (5) can be expressed as:

$$TL(S_1, S_2, ..., S_m) = \sum_{i=1}^{m} L(S_i) - \sum_{k=2}^{m} \sum_{\substack{S' \subseteq S \\ |S'|=k}} \sum_{\substack{S'' \subseteq S \\ |S''|=m-k \\ S'' \cap S' = \emptyset}} (sel^{m-1}(k-1) \prod_{a \in S'} Lr(a) \prod_{b \in S''} m(b)) \quad (9)$$

The completeness C of a $S_1 \bowtie S_2 \bowtie .... \bowtie S_m$ join query, using the general form of (1) and equation (9) is:

$$C = \frac{T(S_1, S_2, ..., S_m) - TL(S_1, S_2, ..., S_m)}{T(S_1, S_2, ..., S_m)} \quad (10)$$

Developing expressions in (10) allows us to simplify C to:

$$C = \frac{n^m \prod_{i=1}^{m} m(S_i)}{\prod_{i=1}^{m} W_i \lambda_i} \quad (11)$$

and to obtain

$$n = \sqrt[m]{\frac{C \times \prod_{i=1}^{m} W_i \lambda_i}{\prod_{i=1}^{m} m(S_i)}} \quad (12)$$

It is clear from our analysis that (11) is independent of selectivity which is reasonable in the context of continuous join queries. As our analysis shows, DHTJoin can scale up the processing of continuous join queries using multiple

peers and improve the completeness of join results. Using (12) a DHTJoin user can adjust the size of the network by evaluating how many peers are necessary to process a continuous join query for given stream arrival rates and a desired result completeness.

6 Dealing with Data Skew

DHTJoin relies on a hash function to distribute data streams in the DHT using join attribute values. So far, we assumed that the hash function yields uniform distribution of the join attribute values. However, it is well known that parallel join algorithms suffer from join attribute skew, i.e. certain join attribute values are much more frequent than others [27], which hurts load balancing and thus response time. It is important to note that data skew occurs naturally in many data streaming applications [39]. For example, in online analysis of transaction logs generated by telephone call records, some numbers used for online tv contests register a huge number of phone calls. In network monitoring applications, malicious traffic traces show that an abnormally high number of source addresses are connected to a single destination address. In DHTJoin, data skew in join attribute values may hurt load balancing of join execution. Furthermore, it may reduce the completeness of join results because the overloaded nodes cannot maintain all received tuples in their sliding window.

In the context of parallel join algorithms, specific solutions have been proposed to deal with data skew. A common solution is to capture join attribute distribution [15][38][21]. However, this requires scanning the joined relations before join execution which is not feasible with continuous data streams. The sampling solution proposed in [10] is also not possible since the arrival of tuples in an arbitrary interleaved way makes the sampling imprecise.

Therefore, we propose a new solution to deal with data skew. The key idea is to distribute the tuples of an overloaded node to some underloaded (or lightly loaded) nodes, called *partners*. There are several issues to address: 1) How to determine that a node is overloaded; 2) How to find partner(s) node(s); 3) What data to migrate and how to execute a join query Q; and 4) When to start data redistribution.

We say that a node is overloaded if it is not capable of storing all arriving tuples that are not expired. Recall that a load shedding process eliminates stored tuples before they are expired. Each node has a memory space assigned to store tuples belonging to each stream. Thus, detecting whether a node is overloaded is made locally. A node considers that the redistribution of tuples to a *partner* node must begin when a certain threshold δ is exceeded. Let c_n be the storing capacity of node n, i.e. the number of tuples it can store, and s_n be the number of tuples it actually stores. Then, a node n is considered as overloaded when $\frac{s_n}{c_n} > \delta$, where $0 < \delta \leq 1$.

Once a node n becomes overloaded, it should find a *partner* node. For this, it contacts the nodes in its finger table. Each contacted node sends its free

storing capacity and the *partner* is the closest node (with smaller latency) whose free capacity is higher than the requirement of n. If there is no *partner* with enough free capacity to store the tuples of n, several *partners* are chosen from the finger table.

We use the concept of domain partitioning over the join attribute in order to determine what data to send to the *partner(s)* node(s). Consider an attribute a be a join attribute belonging to stream S_i and let D_a be its domain of values. D_a is partitioned into m nonempty sub-domains $d_1, d_2, ..., d_m$ such that their union is equal to D_a and the intersection of any two different sub-domains is empty. When a node is not overloaded, it is responsible for the entire domain D_a of the join attribute. Once a node n is overloaded, the domain is partitioned uniformly into two sub-domains, e.g. d_1 and d_2, and a *partner* node is selected, e.g. n_1. Node n gets responsible for the sub-domain d_1 and *partner* node n_1 gets responsible for the sub-domain d_2. Each overloaded node constructs a local index that stores the upper and lower bounds of the generated sub-domains and the address of their respective responsibles. When one *partner* is not capable of storing the tuples of the overloaded node n, several partners are chosen and the index of n is set accordingly.

If a *partner* n_1 becomes overloaded, it informs n. Then, node n reorganizes the sub-domain of which n_1 is responsible by dividing it and searches among its neighbors for a new responsible n_2. The index is then updated with the new reorganization of sub-domains and node n_1 is contacted in order to inform it that tuples must be sent to node n_2. Thus, the responsability of the sub-domain is shared between n_1 and n_2.

To execute a continuous join query $R \bowtie S$, the overloaded node n executes the same steps as in the non-overloaded case for each incoming tuple $r_i \in R$, with only one additional access to the local index: 1) r_i is used to purge tuples in S stored at the partner node registered in the index, 2) r_i is probed with tuples in S stored at *partner node(s)* registered in the index, and 3) the value of the join attribute of r_i is examinated and r_i is stored in the node indicated by the index. The same steps are executed for a S tuple.

In summary, to obtain a join result DHTJoin must first index each incoming tuple which incurs $O(logN)$ messages (see Section 3.2). Then, if a node is overloaded, it redistributes tuples to a *partner* node. The redistribution adds only one message per tuple (to send from the overloaded node to the partner node).Thus, to obtain a join result DHTJoin uses $O(logN) + 1$ messages, keeping the response time slow.

7 Performance Evaluation

In this section, we provide an extensive performance evaluation of our method through simulation, compared with a baseline method.

Simulator. To test our DHTJoin method, we built a Java-based simulator, using Chord which is a simple and efficient DHT. We use a discrete event simulation package SimJava to simulate the distributed processing. The network

size is set to 1024 nodes. To simulate a node, we use a Java object that performs all tasks that must be done by a node in the DHT, in the dissemination procedure and in the join query processing. In order to assess our approach, we compare the performance of DHTJoin against a complete implementation of RJoin. [17] which is the most relevant related work (see Section 8). RJoin uses incremental evaluation based on tuple indexing and query rewriting over distributed hash tables. In RJoin a new tuple is indexed twice for each attribute it has; wrt the attribute name and wrt the attribute value. A query is indexed waiting for matching tuples. Each arriving tuple that is a match causes the query to be rewritten a nd reindexed at a different node.

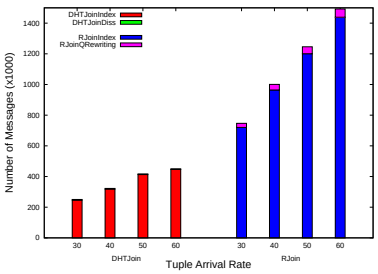
Data generation. We generate arbitrary input data streams consisting of synthetic asynchronous data items with no tuple-level semantics. We have a schema of 10 relations, each one with 10 attributes. In order to create a new tuple we choose a relation using an uniform distribution and assign values to all its attributes using a Zipf distribution with a default parameter of 0.9. The max value of the domain of the join attribute is fixed to 1000. Unless otherwised specified, tuples on streams are generated at a constant rate of $\lambda_i = 30$tuples/second .

Query generation. Unless otherwise specified, queries are generated with a mean arrival rate of 0.02, i.e., a query arrives to the system every 50 seconds on average. We generate queries of type 1 to evaluate the tuples' arrival rate and query's arrival rate. The effect of number of joins was evaluated using queries of type 2. In all experiments, we use time-based sliding windows of 50 seconds. The default duration of our experiments is 300 seconds.

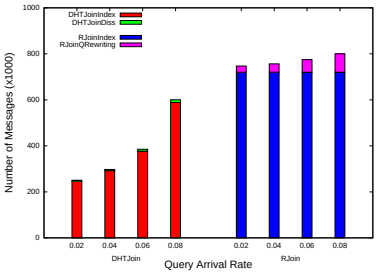
In the rest of this section, we evaluate network traffic and the effectiveness of the approaches proposed in Section 4 to deal with node failures.

7.1 Network Traffic

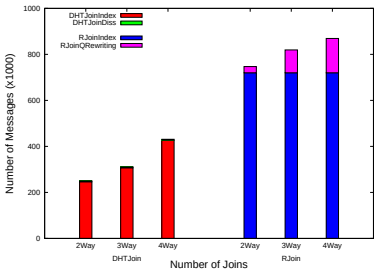
In this section, we investigate the effect of tuples' arrival rate, query's arrival rate and number of joins on the network traffic. The network traffic is the total number of messages needed to index tuples and disseminate a query in DHTJoin or to index tuples and perform query rewriting in RJoin. The network traffic of RJoin and DHTJoin grows as the tuples' arrival rate grows. In RJoin, as more tuples arrive, the number of messages related to the indexing of tuples and query rewriting increases (see Figure 7(a)). DHTJoin generates significantly less messages than RJoin. The reason is that before indexing a tuple, DHTJoin checks for the existence of a query that requires it, but RJoin indexes all tuples twice (even if there is no query for them). In Figure 7(b), we show that, as more queries arrive, RJoin generates more query rewriting messages. However, DHTJoin generates more messages only if new submitted queries contain attributes not prese nt in the set of predicates $\mathcal{P}$ of already submitted queries. Figure 7(c) shows that more join require more network traffic. RJoin generates more query rewriting when there are more joins in the queries. However, in DHTJoin the network traffic increases only if the arriving



(a) Effect of tuple arrival rate



(b) Effect of query arrival rate



(c) Effect of number of joins

Fig. 7: Effec of tuple, query arrival rates and number of joins on the network traffic

queries require attributes that are not present in the already disseminated queries. The reason is that with the dissemination of queries, DHTJoin can avoid the unnecessary indexing of tuples that are not required by the queries.

In summary, due to the integration of query dissemination and hash-based placement of tuples our approach avoids the excessive traffic generated by RJoin which is due to its method of indexing tuples.

7.2 Node Failures

We now investigate the effect of the approach proposed in Section 4.2 in order to deal with node failures during query execution. In our experiments, we repeat the same scenario of Figure 1 with $\lambda_i = 400$tuples/sec. In Figure 8, we show that, as the period of inactivity (time between fail and recovery) of a stream source gets longer, the generation of tuples that never contribute to join results increases. However, by eliminating unnecessary intermediate results, this optimization yields an important reduction of network traffic.

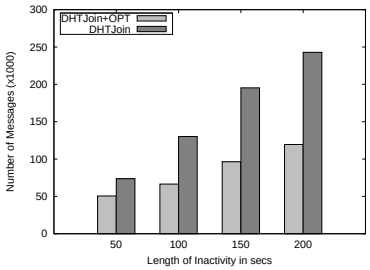


Fig. 8: Reduction of intermediate results and its impact on network traffic

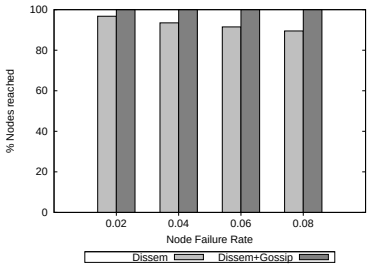


Fig. 9: Effect of dealing with node failures during the dissemination procedure

7.3 Failures During Dissemination

The failure of a node in the tree structure generated by the dissemination procedure makes the entire subtree under this node unreachable. To provide reliability in the dissemination of queries, we proposed a gossip based protocol (see Section 4.1). To evaluate the effectiveness of our approach regarding an increment of node's failure rate we originate queries every 100 seconds on average and we increment the node's failure rate (see Figure 9). We consider a first scenario where the queries are disseminated using the technique described in Section 3.1 and a second scenario where the queries are disseminated using the same technique in complement with gossip. Figure 9 shows that with node failures the dissemination cannot achieve a network coverage of 100%. However, the dissemination of queries complemented with gossip can obtain a network coverage of 100% in spite of an increase in n ode failures.

8 Related Work

Unstructured P2P networks typically use a simple flooding scheme which is inefficient in terms of response time and consumes much network traffic. Furthermore, they are not suitable for efficient processing of continuous join queries as they do not provide guarantees of any kind. Structured networks (i.e. DHT) provide more efficient key-based search. Because applications that process streams from different sources are inherently distributed and because distribution is a well accepted approach to improve both performance and scalability [8][35] of a DSMS, using a DHT is a natural choice to face the challenges motivated by the processing of continuous join queries. DHTJoin exploits the power of a DHT in two major ways. First, to disseminate queries using a tree based on the information stored in the DHT routing table. This information is maintained by the DHT protocol and does not entail any extra processing cost for DHTJoin. In a network of n nodes, the dissemination generates $n-1$ messages and a tree of depth $log(n)$, which bounds the latency of query dissemination. Second, to index tuples for query processing and detect a failure on a node that participes in query processing tasks.

A DHT can serve as the hash table that underlies many parallel hash-based join algorithms. However, our approach provides Internet-wide scalability. Our work is related to many studies in the field of centralized and distributed continuous query processing [16][12][36][6][24]. In PIER [16], a query processor is used on top of a DHT to process one-time join queries. Recent work on PIER has been developed to process only continuous aggregation queries. PeerCQ [12] was developed to process continuous queries on top of a DHT. However, PeerCQ does not consider SQL queries and the data is not stored in the DHT. Borealis [36], TelegraphCQ [6] and DCAPE [24] have been developed to process distributed continuous queries and many of their technique s for load-shedding and load balancing are orthogonal to our work. In Seaweed [25] a scalable query infrastructure built on top of a DHT to process one-shot queries rather than continous queries. However, Seaweed does not use the DHT to distribute data but to replicate metadata and to disseminate queries. An algorithm for suporting ranked join queries in P2P networks was introduced in [42]. Irrelevant top-k tuples are pruned of local nodes before they are sent to be probed for join matches. However, this work does not consider continuous queries. The most relevant previous work regarding the utilization of a DHT network to process continuous queries is [17] which proposes RJoin, an algorithm that uses incremental evaluation. This incremental evaluation is based on tuple indexing and query rewriting over distributed hash tables. A major difference in our work differs is that DHTJoin avoids indexing tuples that cannot contribute to generate join results and deals with the dynamic behaviour of peers.

To disseminate a query, DHTJoin dynamically builds a dissemination tree as proposed in [11]. However, this work does not consider the dynamic behaviour of nodes. To solve this problem, we propose a gossip-based solution that considers the utilisation of the neighbor list to provide fault tolerance. The probabilistic dissemination algorithm Randcast proposed in [20] spreads messages very fast but fails to reach every node in the network. The protocol proposed in [22] assures a good tradeoff between message overhead and reliability guarantee using a specific connection graph. However, its main drawback is the maintenance of such graph that requires global knowledge of membership. In our work, the structure that supports the membership protocol is supported by the DHT and does not require global knowledge of membership for its maintenance.

Result completeness has been studied in the context of P2P databases. A solution to estimate the completeness has been proposed in [19] for one-time queries. Completeness is computed at the peer level using the notion of routing graphs. The routing graphs trace the routes that a one-time query and its sub-queries take through the network. In the Seaweed query infrastucture [25], data summaries and availability models are used in order to predict query completeness and response times to one-shot queries. Our work instead considers continuous queries and completeness is calculated at the data level, which is finer grain and more precise than with data summaries.

A final problem when using hash-based join algorithms is join attribute skew, i.e. some join attribute values may appear much more than others in tuples. In the context of parallel databases, join attribute skew hurts load balancing of parallel join execution, with some nodes getting overloaded while others remain underloaded. To address this problem, parallel join algorithms have been refined over years to deal with data skew in specific ways [27]. A major solution to handle join attribute skew is to capture join attribute distribution which requires require scanning the joined relations before join execution [15][38][21]. In the context of data streams, where queries are executed continuously and tuples arrives at high rate, scanning completely a relation is no longer feasible. The algorithm proposed in [10] attempts to solve this problem by sampling the inner relation before the join begins. However, in data streaming applications, tuples arrive in an arbitrary interleaved fashion which makes sampling unprecise. Our solution is novel and chooses at run time *partner* nodes to store the tuples of the overloaded nodes, using information of the routing table.

9 Conclusion

In this paper, we proposed a new method, called DHTJoin, for processing continuous join queries using DHTs. DHTJoin combines hash-based placement of tuples and dissemination of queries using the trees formed by the underlying DHT links. DHTJoin takes advantage of the indexing power of DHT protocols and dissemination of queries to avoid the placement of tuples that cannot contribute to generate join results. We showed analytically that DHTJoin can scale up the processing of continuous join queries using multiple peers and improves the completeness of join results linearly as the memory capacity is increased.

We also addressed the problem of join attribute skew which may hurt load balancing and yield the loss of result tuples at overloaded nodes. Our solution chooses at run time *partner* nodes to store the tuples of the overloaded nodes, using information of the routing table. It keeps response time low, adding only one message to produce each join tuple.

To validate our contribution, we implemented DHTJoin, as well as RJoin which is the most relevant state of the art solution in the context of processing continuous join queries using DHTs. Our performance evaluation shows that DHTJoin yields significant performance gains due to the mechanims of indexing tuples and the elimination of unnecessary intermediate results. Our results also demonstrate that the total number of messages of DHTJoin is always less than that of RJoin wrt tuple arrival rate, query arrival rate and number of joins. We show that the problem of node failures during the dissemination of queries can be complemented with a gossip based protocol that allows, in spite of node failures, a network coverage of 100%. We also showed that our approach to deal with node failures during query execution prevents nodes

of sending intermediate results that do not contribute to join results, thereby reducing network traffic.

As future work, we plan to address the problem of efficient execution of top-k join queries over data streams using DHTs, taking advantage of the best position algorithms [1] which can be used in many distributed and P2P systems for efficient processing of top-k queries.

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