A Scalable Stream-Oriented Framework for Cluster Applications

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ABSTRACT
This paper presents a stream-oriented architecture for structuring cluster applications. Clusters that run applications based on this architecture can scale to tenths of thousands of nodes with significantly less performance loss or reliability problems. Our architecture exploits the stream nature of the data flow and reduces congestion through load balancing, hides latency behind data pushes and transparently handles node failures. In our ongoing work, we are developing an implementation for this architecture and we are able to run simple data mining applications on a cluster simulator.

1. INTRODUCTION
One of the main characteristics of computing these days is the data explosion; in fact, data nowadays grows at an exponential rate. What is really surprising, however, is that the growth of the acquired data surpasses the increase rate of the processing speed of today’s processors. As an example, the amount of data in GenBank (a genomics database) doubles every 9 months, a much higher rate than the 18-month doubling period of processors (as dictated by Moore’s law). On the other hand, the processing of data is of imminent value, since we continuously discover new ways to mine and process large amounts of data to extract useful information. Fields such as biology, physics, earth sciences and even marketing depend more and more on mining huge amounts of data to break new ground and advance forward.

Where all this leads to is that we need to find a way to process ever-larger amounts of data with systems of reasonable cost. A possible solution to this problem could be clusters of commodity machines; after all, the cost of PC and network hardware keeps falling at impressive rates. Thus, one would argue, all we have to do to reach our goal is to buy more PCs, larger switches, and just connect everything together.

Unfortunately, there are multiple problems when we try to follow this approach. First, there are severe scaling problems. Indeed, utilization of under 10% of peak performance in large Linux clusters has been reported [†]. The problem has only begin to show up in current systems, since the majority of today’s clusters has relatively small sizes between 10 and 100 nodes, with only a handful of systems being in the range over 1000 nodes. However, in order to cope with the rapidly increasing amounts of data, we should expect that clusters with many thousands of nodes will become the rule rather than the exception in a few years; moreover, clusters with 10,000 nodes or more should start appearing soon. One can only imagine how severe scaling problems will appear in systems of such size.

Apart from performance problems, today’s cluster face a number of other challenges. Node failures is one of them. Basic probability theory dictates that the more nodes we have in a cluster, the greater the chance that one of them will fail within a small period of time. Identifying and correcting node failures is a hard task that today usually requires human intervention. Moreover, writing an application to run on a cluster, even a simple one, is much harder than it seems. With today’s technology one has to use some sort of message passing interface or start making remote procedure calls to transfer data. Such programming is difficult, time consuming and hard to debug, especially in a parallel environment.

The question that naturally follows is what can we do about these problems. More specifically, how should the data be send between the nodes so that congestion and latency problems do not arise? How do you deal with node and network failures that are inevitable in a system of that size? What’s the most effective way to interconnect such a big network? And last but not least, how can one program and debug such large scale applications? On a first thought, these questions seem orthogonal to each other and inherent in every large scale system.

However, we believe that this is not true. We claim that the problem lies in the conventional way that today’s systems are engineered, and that an integrated solution to all of the above questions do exist. Specifically, today’s systems are build under the convention that the applications determine data flow in an arbitrary way. What this means is that a part of an application that runs on a cluster node can potentially request data from any other node at any time; and under this assumption, there is no systemic action that
can be taken to prevent scaling problems. Viewed from a point outside of the application, data requests are random accesses, and random access does not scale.

The solution that we propose is to build the whole system based on *streams*. More specifically, we propose to structure the applications in a way that they read and write streams and build an underlying framework that handles all the data flow issues. There are numerous advantages that result from this approach. By infusing the stream model into the applications, we can build a framework that has enough knowledge of how the data flows within the cluster to circumvent the scaling problems. Instead of using data requests to send data from one node to the other (a latency-prone approach), data can now be *pushed* to its destination beforehand.

Moreover, this model significantly simplifies applications programming. Issues that before needed to be handled by the application, such as data flow and node failures, are now handled transparently to the application by our framework. Since all data exchange takes place using structures similar to files, there are no complicated message-passing code that is hard to write, prone to errors and sensitive to changes (e.g. in the size of the cluster).

Finally, node failures become manageable since the framework has enough information to figure out what part of the data is lost and proceed to corrective action. This way, every application that is written using streams is robust to failures, at no expense to the programmer.

In the rest of this paper, we present our on-going work which can be separated to two main tasks. The first is to define the computational model of streams: their programming representation and their semantics. The second task is the implementation of the programming framework that includes functions such as stream operations and node failures handling. We begin by presenting the streams model.

## 2. The Streams Model

The goal of our system is to perform efficient processing on large amounts of data. We refer to an independent and complete processing application as a *task*.

An interesting observation is that in most cases a task can be broken down to a number of independent operations that apply on data as it flows through them. More specifically, we define a computational *stage* to be a logical processing unit: each stage receives as input a number of streams, and it has the option to apply some specific operations to the incoming streams. As an example, a stage could specify that it needs to receive a particular stream *sorted* in some sense (we will define exactly what this means in the next sections). The stage then can perform any computation on the data units of a stream, and it can output the results of the computation as another set of streams, for the next stages to process. For an illustration of this concept see figure 1.

![Figure 1: In this example we have three stages. Stage 1 outputs streams “streamA.str” and “streamB.str”. Stage 2 inputs “streamA.str” and stage 3 inputs “streamB.str”. Note that all details of how stream data is delivered to nodes are handled by the framework.](image)

An important point here is to distinguish between the *declaration* and the *definition* of a stage. More specifically, a stage declaration is comprised by:

1. the declaration of the input streams (which must be provided by previous stages),
2. the declaration of the operations that should be applied on the input streams, and
3. the declaration of the output streams.

Additionally, a stage definition includes the actual function that operates on the data units that a stream carries.

The reason why this distinction is important has to do with the fact that the flow of data depends on the declaration of a stage solely. In other words, we can determine with which other stages a stage will exchange data. Thus, the layout of the data flow is now known before the execution of the application, just by examining the declarations of the stages.

A question that naturally arises is how are stages related to nodes? This issue will be examined in the implementation section, but as a simplification one can imagine that each stage is assigned to a set of nodes with each node in the set running the *same* piece of code (specifically the stage function that operates on the stream data units).

### 2.1 Definition of Streams

“Streams” of data have been around since the first days of computing. Usually, when one refers to a stream, she implies a data flow with two main properties: sequentiality and uniformity. That is, a stream can be abstracted as a sequence of *data units* with the restriction that these data units are of the same kind (i.e. they share a common low-level data representation). As an example, one could naturally define
“a stream of integers” to mean a data sequence with data units being 32-bit integers.

In our model, we have expanded this classic definition of streams. We raise the restriction of sequentiality, in the sense that in some cases the exact order of data is of little importance. For example, we may have three nodes sending data to another three nodes using a single stream (see figure 2): because the three sending nodes are not synchronized, order is difficult to be determined here. The other extension to the streams definition is that our model requires each data unit to be associated with a key. We can describe the key to be just a constant-length additional field to each stream unit. Thus, each unit of a stream can be abstractly described as a C struct:

```
struct StreamDataUnit {
    KeyType key;
    DataType data;
};
```

Although the data field could change depending on the DataType that a stream is associated to (i.e. the type representation of a stream’s data units), the type of the key, KeyType is the same for all streams. Intuitively, key is a numeric field that in some way acts as a representative for the respective data in the various stream operations. In our current implementation, KeyType is a fixed-size 64-bit integer.

Additionally, one soon realizes the need to uniquely identify every stream. Towards this purpose, we define a global stream namespace where each stream is associated with a unique name. We conventionally refer to streams with names that end in “.str”, but essentially any unique string is adequate. Having all streams under a unique namespace is an important simplification, since if a stage outputs a stream named “sorted.str”, then another stage that is interested in processing this stream just needs to “ask” for the stream named “sorted.str” (more details on the programming interface are provided in section 3).

### 2.2 Stream Windows

Streams have infinite length in theory, and usually unknown length in practice. Since most applications simply need results before the end of the stream, we need to find a way to start producing results while a data stream still flows. As a solution to this, we propose using stream windows as computational units, upon which we can perform operations and produce results. There are many ways to define such a window; what we have used, and seems to make sense for a large number of applications, is to define a window based on a timestamp. This timestamp is defined as a non-negative integer and it is set by the programmer in the stage where the data is produced. It has the additional requirement that it should be increasing; that is, stream data units that are outputted first (at a stage’s output stream) are expected to have smaller timestamps than the data units that follow. More formally, a window of width T is defined to be all the data units of a stream that have timestamps more or equal to nT and less than (n + 1)T − 1, for n ∈ ℤ. As an example, the first window will be all the stream data units with timestamps 0 to T − 1 and the second will have data units with timestamp from T to 2T − 1.

Having defined the notion of window, we now proceed in defining the stream operations.

### 2.3 Operations on Streams

As mentioned before, each stage can apply some operations on the incoming streams. One could see these operations as a kind of “queries” on streaming data. The reason why our framework provides these operations (instead of having the applications programmer providing them) has to do with the need of the framework being in control of how the data flows. In a conventional approach, the application programmer would need to program both the data flow operations (e.g. using a message passing interface) and the operations that apply on the data units. Our approach, in contrast, is to distinguish these two programming tasks, provide the data flow operations by the framework and leave up to the programmer the simpler but more important task of programming the data operations. In this way, we achieve both to give the framework full knowledge and control of the data flow and to relieve the application programmer from the hard task of programming how the data should move from one node to the other.

In deciding which operations should be provided by the framework, we wanted to select a relatively small operations set that would cover the majority of our target applications. These operations act on windows of data, as defined in the previous section. More specifically, these operations and their semantics when applied to a stream are:

**Sort** For each window, the data units of the operated stream
will arrive at each node at a sorted order (either descending or ascending) based on the key value.

**Group** For each window, the data of the operated stream will arrive at each node grouped by the key value, i.e., all stream data units of the same window that have the same key value will arrive together at each receiving node.

Figure 3 shows an example of the Group operation. There we have packets of a stream flowing from the left three nodes to the right three nodes. The stream has the Group operation applied to it, and thus packets with the same key end up at the same node.

We argue that these two simple operators suffice for a surprising large number of applications. Indeed, in many data processing applications data is exchanged between the nodes of a cluster in order to be grouped, to be sorted or to perform a seemingly different operation that on a hindsight it is again based on sorting or grouping.

There is a large number of operations that can be implemented using our two basic operations combined with some in-stage computation. Here are some examples:

- **Join.** We can perform window-oriented joins between streams of data. By join we mean that we output a concatenation of data units from the joined streams if all these data units share the same key value. The way that this can be implemented is that we create a stage with input the streams that we would like to be joined with the Group operation applied. Then all the data units with the same key value will end up at the same node. All we have to do then is to see which of these key values span across all streams and output the respective data units.

- **Select.** A select operation can also be implemented. By select we mean that we want a stream to contain only key values that satisfy a specific criterion (perhaps a boolean formula). In order to implement this for a stream, we just add some code at the stage that outputs the stream that only allows a data unit to be outputted when it satisfies the mentioned criterion.

- **Aggregations.** Assume that we have a stream and we want to perform some aggregation operation on it, e.g., if the stream carries integers we may want to sum all integers in each window. One way to implement this is to define a stage that takes the stream to be aggregated as an input, defines another output stream that carries the aggregations and have that stream end up in the same node (by giving each aggregation the same key and applying the Group operator) where all the aggregations would sum up to produce the final number for each window.

One could argue whether these functions should be classified as stream operations or simple applications. The point, however, is that the Group and Sort operations with data units computations is a much more powerful combination that what it seems.

### 2.4 Load Balancing using Failure Management

There are two reasons why a node may get overwhelmed with data:

- The node may have lower performance compared to the other nodes due to a hardware/software problem. This is the classic definition of “node failure”.

- The actual amount of data send to the node may be much greater than the amount send to other nodes; thus although the node functions properly, it can not process all the incoming data as fast as the other nodes.

In our approach we do not distinguish between these two cases, although they may seem initially as two totally different problems. We argue that by using the failure recovery mechanism for both cases is the more appropriate tactic for the following reasons.

- In many situations it is hard to distinguish between the two cases; thus by treating data overloads and failures differently, there is the risk of making a wrong decision and make the problem worse instead of fixing it.

- On an afterthought, the two problems are very similar in nature; indeed, the result of both is that a node is not able to finish a task that it has been assigned; thus the appropriate corrective action in both situations should be also very similar.

- Some load balancing mechanisms are anyway implemented into the failure management subsystem since after a failure occurs, the failure must be handled in a way that will not result in making other (non-failed) nodes overloaded.

- The design of the system is overall simpler and more effective when we can solve two important problems under a single mechanism.
• Under our approach, load balancing takes into consideration all possible causes of load unbalance, such as failures, bad data partitioning, non-uniformities in hardware or network and corrects them in run-time.

We thus believe that the above are significant advantages of our approach compared to other conventional load balancing mechanisms. Note that the definition of failure that we use, i.e. a node that does not make adequate progress, means that our load balancing mechanism can handle not only problems of data partitioning and overloading, but also hardware and network problems (since e.g. a bad network link would also cause slow node progress). More details on the implementation of the above mechanisms are given in section 4.7.

3. PROGRAMMING FRAMEWORK
In this section we present the programming framework that provides the applications with the streams functionality. The approach that we have taken is to implement the framework as a C++ library, that is compiled along with the application code.

More specifically, the programmer needs to perform two main tasks in order to build a cluster application:

1. The high level stage and stream declarations must be given. That is, the stages and the streams must be created and then each stage must specify which are the input and the output streams that it uses and what operations should be applied into the incoming streams.

2. For each stage, the programmer must provide the actual function that performs the computation on the data units, that is reads the data from the incoming streams, modifies it and outputs the results to the outgoing streams.

3.1 Stage and streams declarations
Our aim is to declare stages and streams in a single point within the code. In our current implementation, the programmer needs to create a function where stages and streams are declared as in the following example:

```cpp
Ptr<Stage> processingStage =
    stageManager->newStage(10);
```

where the number 10 declares the nodes to be assigned to this stage. Also, a stream is declared similarly as

```cpp
Ptr<Stream> dataStream =
    streamManager->newStream("data.str");
```

where the name of the stream is declared. After both a stage and a stream is declared, the fact that the stage is associated with a stream should be declared as well:

```cpp
processingStage->newOutputStream(dataStream);
```

or

```cpp
processingStage->newInputStream(dataStream, SORT);
```

where in the second case, the second argument is the operation to be applied to the input stream.

3.2 Stage function definition
In our approach streams share many characteristics with files. In order to read or write data from a stream, one has to call the `getStreamHandle()` method that takes as an argument the string name of the stream and whether it is an input or an output stream. Here are some examples:

```cpp
StreamHandle distrStr =
    getStreamHandle("distr.str", INPUT);
StreamHandle mergeStr =
    getStreamHandle("merge.str", OUTPUT);
```

Using the `StreamHandle` objects one can get or send packets from/to the respective streams. For instance, the expression

```cpp
data = getPacket(distrStr);
```

would get the next packet from the queue of the stream "distr.str". Similarly, in order to send a packet to the stream "merge.str" one simply has to issue the command

```cpp
sendPacket(mergeStr, data);
```

In both these examples, data is of type `DataUnit`, which is the class representation of a stream packet.

Note that in our implementation there is also a notification mechanism for signaling the stage function when new packets arrive.

4. IMPLEMENTATION
We are currently implementing a framework that will support cluster applications that use the stream model. To test and evaluate this framework we are also developing a simulator of a cluster. In the next sections we present the details of the framework implementation and the simulation environment.

4.1 Simulation Environment
As mentioned before, we have developed a simulation environment to test and develop our framework.

The lower layer of the simulator is the network, where nodes and their interconnect are simulated and a basic mechanism to exchange packets exists. Packet traffic is implemented using queues for each node and event notifications.

We are currently progressing towards implementing the full functionality of the framework as described in this paper. As a future work, we plan to deploy it in a small-size real cluster for further development and testing.
4.2 Data flow
As mentioned before, an important advantage of the stream model is that data can be pushed to its destination, instead of having to be requested in advance. In order to do this, we are using TCP connections; actually, TCP fits our needs pretty well since it is stream-oriented in nature.

There is the issue of how we create and manage the connections from the application point of view. The case in most of today’s systems is that the programmer needs to explicitly identify which connections must be created and between which nodes specifically (e.g., one may need to specify the IP’s of the nodes). However, in our implementation after the declaration of stages and streams is done, a connection is created automatically by the framework for every pair of nodes that exchange data using a specific stream. The ID’s of the connecting nodes and all the other network details are hidden behind the simple specifications of stages and streams.

To analyze this in more detail, when a stage is declared, the number of nodes it is assigned to is also declared. Each of the assigned nodes receive an initialization packet that includes the streams that it inputs and outputs along with the IP’s of the nodes that it should be connected through these streams. Then the node opens a TCP connection with each node that is connected through a input stream and listens for a connection from each node that is connected through an output stream.

When a node has made all the connections for its input and output streams, it can start its computation. As soon as there is some results from a stage, the nodes of that stage push the data to its destination; for flow management we use the standard TCP flow control mechanisms. Consecutively, as soon as the next stages receive the first data packets, they start processing data and producing results.

4.3 The Control Process
As soon as one tries to implement some control features, such as failure management and load balance mechanisms, it becomes evident that we need to synchronize the cluster nodes on some decisions. As an example, in order to classify a specific node of a stage as failed, all nodes of the previous stage must agree on that fact; otherwise we may end up in the unfortunate situation where some part of the data still goes to the failed node (by the nodes that do not see it as failed) while other nodes (that consider it failed) send related data elsewhere.

In order to implement such features, a node is automatically chosen to host a control process and it is called the control node. This process communicates with the nodes of each stage, receives data and feedback from them and makes decisions such as whether a node should be considered failed or not (failure management) or how the data should be partitioned to be send to the receiving nodes (load balancing).

Note that we can have one control node per stage or one control node for all stages or something in between. In other words, a physical node can run as many control processes as it can manage; we expect that the control tasks will not be demanding in terms of processing power and bandwidth requirements and thus a single node can act as a control process for many stages. For an example of this fact, see figure.

4.4 Windows-based Computation and Implicit State
In section 2.2 we argued on the need to have windows as a computation unit. Implementation-wise, what this means is that our total computation task is actually a sequence of small window computations. Under this model, state is directly related to windows: the framework assumes that the data of a window are its implicit state. Therefore, during a window computation the only data (state) that needs to be preserved is the data of the current window. This model enables us to perform load balancing and failure management transparently, since the application does not have to declare explicitly what state should be recovered in case of a failure.

4.5 GROUP Operation
In the Group operation three entities are involved: the sending stage, the receiving stage and the Group’ed stream. Remember that the semantics of the Group operation is that we need all stream data units with the same key to end up at the same node.

The main challenge in implementing the Group operation is how to partition the keys in a way that no node gets either overloaded (by receiving too much data) or stays idle (by receiving too little data). Related work in this field proposes to make a pass over the data before deciding on how to distribute it. However, in our case this is too expensive and often impossible since we do not have the luxury to store the (possible endless) incoming stream data in order to determine the distribution; let alone the fact that determining the actual distribution would require sorting the data, which brings us back to our initial problem of how to split the data.
To tackle this problem we implement the following strategy. As soon as some data is produced in the sending nodes, instead of streaming it to the next stage we buffer it and measure its distribution. The sending nodes use this information to determine how the data should be split among the nodes. After we begin sending data, we consider any overloaded nodes as failed and use our failure handling mechanism to redistribute the data of these nodes.

Let’s see the above procedure with some more detail. First, we partition the data units using a hash function. Note that we partition based on the keys of the data units, and thus we ensure that data units with identical keys end up in the same node. A problem that arises is that we do not know the size of each partition in advance; nor we can assume that all partitions have equal sizes. The way we solve this issue is by making the number of partitions a multiple of the number of nodes of the receiving stage; in other words, we hash the data to a number of buckets that is many times the number of the nodes that these buckets will end up to. By carefully assigning many buckets per node we are able to circumvent the problem of buckets having different sizes.

However, we can not make a proper assignment of buckets to nodes if we do not know the size of each bucket. In order to get an estimate of this, we do not start sending data as soon as it is available; instead, we partition the data locally until a predetermined amount of data has been partitioned. Explain how this is determined. Then, the sending nodes communicate the partition sizes to the respective stage control process (see section 4.6). The control process executes an algorithm that figures out the optimal split of the data (see Appendix A) and returns this information to the nodes that immediately start sending the data to the next stage.

What we achieve with this process is a very good starting point in the computation of the first window. Moreover, before we begin computing the next window we repeat a similar process; but now we can use the actual distribution of the data send in the previous window to best determine how we should split the data in the next window.

However, what if in the middle of a window computation the distribution changes unexpectedly? For example, if we are dealing with a stock trading processing system, a sudden increase in the trading of a specific set of stocks that end up in the same node may overload that node and hold back the whole computation. As mentioned, our solution in this case is to handle overloads as failures. We examine this mechanism in detail in section 4.7.

4.6 SORT operation

The Sort operation share many details with the Group operation. We will describe here in which ways they are similar and we will focus on the points that they differ.

What is traditionally used for sorting data using a cluster of machines is to partition the data into key ranges and assign each range of keys to a specific machine. We argue that under our stream model we can sort in a much more efficient way. More specifically, there are two ways to sort data using a distributed system:

1. We must ensure that each node receives keys that belong to a particular range, e.g. \([\text{min}\_\text{value}, \text{max}\_\text{value}]\). After each node receives all data with keys in that range, it sorts them. Then, whenever some other process needs sorted data that fall into that range, it queries that node. This is the conventional way of sorting data in a cluster.

2. An alternative way is to have the sending nodes sort whatever piece of data they have and then stream out in sorted order the data to the next stage. Each node of the next stage will simply need to merge the incoming data; in other words, if the data is send in descending order, the nodes of the next stage simply need to read each time the data with the highest key from all the incoming connections. This concept is illustrated in figure 6.

We argue that the alternative approach has significant advantages, especially in a streaming environment like ours. As an example, imagine an application that is only interested in the top 10% of the data. With the conventional approach, we need to send all data through the network since we do not know in advance which part of the data will belong in the top 10% (and should be send out) and which not. In contrast, with our approach the nodes will sort the data and they will only stream it out until the next stage is no more interested in reading more data. In other words, no more data is going to be send over the network than what is essential for the computation.

4.7 Failure Detection and Handling

The first step in handling a failure is to detect it. However, since we are building a distributed system, we must make sure that a node must be considered either as failed or not failed by every other node that directly communicate with it. Note that since we have partitioned our computation task into stages, the only subset of nodes that are concerned with a failure are these of a previous stage that send data through a stream to the failed node. Therefore our model achieves to restrict the impact of a failure to only a small subset of the total nodes of the cluster.

Our approach to detecting a failure is that each stage independently decides on whether a node of a next stage is failed or not. The nodes of a stage send periodic progress reports to the stage control process for all nodes where they send data. If there is a node failure then the progress report of all nodes will report that the failed node does not seem to make enough progress; the control process will then characterize this node as failed and it will trigger the failure recovery mechanism.

The recovery mechanism is streams-oriented. This means that the failure will be handled separately for each stream that sends data to this node. The exact actions depend on whether this stream has a Group or Sort operation assigned to it. We begin by looking how to recover a stream with a Group operation.

Assume that we have the stream “data.str” that is distributed Grouped from stage A to stage B. Node n that receives data in stage B fails, and stage A detects that. There
will be a set of key buckets that stage $A$ has associated with node $n$. In implemented a failure recovery mechanism, the following issues need to be solved:

1. The key partition that was assigned to the failed node must be itself partitioned and redistributed to the other nodes without causing any other overloads.

2. The data of the current window that was sent to node $n$ must have been stored somewhere (apart from node $n$).

3. There must be a mechanism to detect which results were outputted before it failed, so that either stage $B$ doesn’t output duplicates or the stage that receives data from stage $B$ can recognize and ignore duplicates.

As soon as the control process decides to declare a node as failed, it also makes a decision of how to repartition the key space. In doing this, it assigns bigger part of the data of the failed node to the nodes that make the greatest progress. In this way, a node failure actually results in a more even load across the nodes of stage $B$. The algorithm to do that is similar with the one for the initial partition (see Appendix A) and it is not presented in detail in this paper.

The data is redundantly stored in the sending nodes. That is, as the nodes stream out data they also buffer it as a back up in case of failures. After the control process has declared a node failed, it determines the new data partition and informs the nodes of stage $A$ that immediately start re-sending the buffered data following the new partition.

We moreover need to detect which results were outputted by node $n$ before it failed, and which not. Since we can not count on the failed node $n$ to give us this data, we should not assign this task in the nodes of stage $B$ to determine this. Instead, with each data unit that we output we include a sequence number that depends on the input data units that were used to produce the specific result. The nodes of the stage after $B$ can check these sequence numbers to simply ignore results that were send to them before by node $n$.

5. RELATED WORK

An other class of related work are database systems for streams. Recently, several stream database systems have been build [?, ?, ?]. However, most of them focus on single-node environments and do not give any insight for implementing such systems in a distributed environment. Moreover, they are focused more on executing pre-determined queries on data rather than acting as a framework for generic cluster applications.

The only database projects that is deals with distributed systems issues in streams databases, to the extend of our knowledge, are the Aurora* and Medusa projects [?, ?]. Note however that these systems are distributed in the sense that two queries can execute in two different nodes – there is no possibility of executing a single query using multiple nodes, something that we attempt to do in our work. Concerning the above systems, in [?], fault recovery is examined in distributed stream database systems. The paper follows a replication-based approach, in contrast to our work. In [?], several approaches on failure recovery are presented and they are evaluated in a simulated environment.

MapReduce [?] is a programming model for writing cluster applications using two functions: the Map function produces some key/value pairs and the Reduce function merges the pairs that share the same key. There are several points where this work differs than ours. First, the streams programming model that we introduce is much more general than simply using a Map/Reduce function pair, since it also includes the notion of windows and operations. Moreover, our system has load balancing mechanisms that are absent from the MapReduce implementation. Finally, MapReduce writes intermediate results to secondary storage (hard disks on nodes) in order to be robust to failures. However, this approach has significant impact on performance. Our aim, in contrast, is to handle failures on-the-fly and use only memory to store intermediate data.
River \cite{river} is a system that uses streams for load balancing. However, load balancing with River can only take place at specific points of the computation; namely, at points where each data unit from one stage can be send to an arbitrarily chosen node of the next stage under no restrictions (this excludes the Group and Sort operations for instance). Our system implements a similar mechanism for load balancing when there are no restrictions in the flow of data; but we also achieve to have load balancing at all stages of our computation, a much more general result. Also, like the River paper, our load balancing mechanism can balance non-uniformities either in data distribution, in hardware or in the network.

As part of the NOW Berkeley project \cite{NOW}, there has been some work on how can one use a cluster to sort efficiently \cite{NOW}. The approach used is to split the data in ranges, that is as we argued in section \ref{sec:bf}, we believe that it is not the best direction to perform a sort operation, at least in our application model. Also, the authors make the explicit assumption that the data follows a uniform distribution; in our work, we do not make this assumption but rather we use data pre-processing to approximate the actual distribution and load balance mechanisms to cope with changes or bad approximations of the actual distribution. Also, our algorithms are position to cope with the case that not all source nodes carry the same amount of data, while this is an essential assumption in the NOW-Sort paper.

There has also been some work on using streams in building faster microprocessors. Specifically, the Imagine stream processor \cite{imagine} uses a stream model to bypass the memory bandwidth bottleneck. Based on the Imagine stream processor, there is an effort by the Merrimac project to build a full supercomputer that is composed of stream processors \cite{merrimac}. We believe that this work differs in goals, assumptions and potential applications from our work. More specifically, Merrimac aim is to achieve an order of magnitude more TFLOPS than conventional supercomputers. However, this greater computing capability requires pure scientific applications that perform a large number of numerical computations and access relatively small amounts of data; our framework, in contrast, enables generic applications that process vast amounts of data to achieve theoretical peak performance in commodity hardware.

APPENDIX

A. SKETCH OF BUCKET DISTRIBUTION ALGORITHM

Consider the following problem: we have a set of buckets, \( \{b_1, b_2, \ldots, b_k\} \), each containing a number of items. Let these numbers of items to be \( n_1, n_2, \ldots, n_k \) respectively. We also have \( l \) nodes. We want to continuously group these buckets into the \( l \) nodes, meaning that each node will get a group of buckets in the form \( \{b_i, b_{i+1}, \ldots, b_{j-1}, b_j\} \). Our goal is to find the bucket grouping that minimizes the variance of the number of items that each nodes receives (in other words, it minimizes the square of the distance of the number of items of each bucket from the average).

In order to try all possible combinations, we would need exponential time, since by applying some basic combinatorics we find that the number of all possible instances of the problem is \( \binom{l+k-1}{k} \). However, there exists a dynamic algorithm solution that solves the problem in polynomial time.

The basic idea of the algorithm is that if we have an optimal distribution of \( k \) buckets into \( l \) nodes, and the \( i \)th node contains up to the \( j \)th bucket, then the allocation of the first \( j \) buckets into the first \( i \) nodes is also optimal. This is true since if it was not optimal, the overall bucket allocation would not be optimal as well.

Based on this observation, we construct a matrix \( T \) of dimensions \( l \times k \). A matrix cell \( T[i, j] \) contains the variance of the optimal allocation for the first \( j \) buckets into the first \( i \) nodes. Also, we have calculated the average number of items per node, \( \mu \). From the mentioned optimality property, we can calculate the \( T[i, j] \) element using values only from the previous column using the following formula:

\[
T[i, j] = \min_{k=1, \ldots, j-1} \left\{ T[i-1, k] + \left( \sum_{t=k+1}^{j} n_t - \mu \right)^2 \right\} \tag{1}
\]

The variation of the optimal solution is \( T[l, k] \). In order to find the actual optimal bucket distribution, we construct a second matrix \( D \) of the same dimensions as \( T \) and in each position we write the minimum decision that we make from expression \ref{eq:1}. Then we can reconstruct the optimal distribution by going “backwards” from point \( D[l, k] \) to \( D[1, 1] \).

The asymptotic running time of the algorithm is \( O(lk) \) to for the outer matrix loop and \( O(k) \) for calculating expression \ref{eq:1} instead of calculating the sum in \( T \) each time, we can initially build an array and cache the sums there. This way, the amortized time to calculate the sum is \( O(1) \). Thus the total running time is \( O(lk^2) \). We have implemented the algorithm and we have found that it executes in reasonable time for values of \( l, k \) near 1000 (e.g., 1000 nodes and 1000 buckets).