A Cooperative, Self-Configuring High-Availability Solution for Stream Processing

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Abstract

We present a collaborative, self-configuring high availability (HA) approach for stream processing that enables low-latency failure recovery while incurring small run-time overhead. Our approach relies on a novel fine-grained checkpointing model that allows query fragments at each server to be backed up at multiple other servers and recovered collectively (in parallel) when there is a failure.

In this paper, we first address the problem of determining the appropriate query fragments at each server. We then discuss, for each fragment, which server to use as its backup as well as the proper checkpoint schedule. We also introduce and analyze operator-specific delta-checkpointing techniques to reduce the overall HA cost. Finally, we quantify the benefits of our approach using results from our prototype implementation and a detailed simulator.

1 Introduction

Recently, there has been significant interest in a new class of applications where high-volume, continuous data streams need to be processed with low latency. Such applications include sensor-based patient monitoring, asset tracking, traffic monitoring, real-time stock analysis, battlefield monitoring, etc. Since these applications monitor real-time events, the value of a result decays rapidly over time. Thus, processing latency is a significant issue.

As a response to these applications, several stream processing research prototypes [7, 4, 8] and commercial products have appeared. In these systems, processing is typically expressed as a dataflow graph of operators. The streaming input data passes through these operators while being transformed on its way to the outputs. This model of processing data before (or instead of) storing it sharply contrasts with the traditional "process-after-store" model employed in conventional database management systems (DBMSs). There has also been recent effort in the area to enhance system scalability by use of inexpensive, commodity clusters [10, 22, 26, 25].

In a distributed stream processing system (DSPS), deploying more servers in general improves the system performance. However, it also increases the risk of failure. In this setting, a failure indeed has a serious negative impact as it blocks the processing that should take place at the failed server. The intrinsic real-time nature of stream processing necessitates a high-availability (HA) solution that enables *fast recovery* and *minimal slow-down of regular processing*.

In this paper, we introduce a novel self-configuring HA approach that significantly outperforms existing ones during both recovery and normal processing. Whereas the previous approaches [21, 14, 5] mask a server failure by failing over to a standby server, our solution enables a set of servers to collectively take over the failed execution, realizing significantly faster recovery. Our solution also has low negative impact on regular processing as it strives to use idle cycles to execute short-duration HA tasks.

To maintain the backups spread over multiple machines, we use *checkpointing* (i.e., incrementally copying the change in state to remote servers) because, as we argue later in sections 2.3 and 8.3, it effectively works for a larger set of workload and usage cases than other alternatives that are based on either replay or redundant parallel execution. For example, checkpointing can tolerate scenarios where the entire system is highly loaded, whereas redundant execution requires at least a half of the cycles to be available.

Our solution involves the following subproblems.

Query Partitioning. Each server needs to partition its query graph into several subgraphs so that each subgraph can be assigned a different backup server. We refer to these subgraphs as *HA units*. We study the problem of forming HA units as well as preserving safety against failures while the system reforms HA units.

Backup Assignment. We need an algorithm that finds an appropriate backup server for each HA unit. Our backup assignment algorithm balances the checkpoint load and minimizes the expected recovery time.

Checkpoint Scheduling. As we rely on checkpointing for HA, we need a method that determines the order and the frequency of checkpoint for HA units. Our scheduling algorithm takes into account the characteristics of HA units such as processing load and checkpoint cost.

In summary, our cooperative, fine-grained HA approach has the following advantages.

1. Since the recovery load is distributed and balanced over multiple servers, the approach facilitates faster recovery than previous ones.
2. Each server checkpoints only a small fraction of its query graph at each step, thereby shortening the duration that a checkpoint blocks regular processing. As a result, the additional latency incurred by HA tasks is kept significantly lower than that of previous ones.
3. Each server strives to fully use its spare CPU cycles (i.e., those left after regular processing) to optimize the recovery performance.
4. If a server fails, each backup server takes over only a fragment of the query graph from the failed server. Thus, after recovery, each server is likely to experience only a small increase in its processing load, thus keeping its latency under control.
5. The framework is adaptive and does not require human administration (e.g., no primary/backup designation).

In addition to the HA solution, we dissect the execution

details of stream operators and develop low-cost checkpoint mechanisms. We also construct analytic models for both checkpoint cost and expected recovery time. Finally, we present prototype- and simulation-based results that substantiate the utility of our work.

The rest of this paper is organized as follows. We provide an overview of the topic in Section 2 and devise our backup framework in Section 3. We discuss HA unit formation in Section 4 and present algorithms for checkpoint scheduling and backup assignment in Sections 5 and 6, respectively. In Section 7, we analyze stream operators and design efficient delta-checkpointing techniques. We demonstrate the experimental results in Section 8 and cover the related work in Section 9. We conclude in Section 10.

2 Background

2.1 Distributed Stream Processing

In stream processing, a query is expressed in the form of a directed acyclic graph of operators that define how to transform the stream data [7, 4, 8]. Some stream operators are directly borrowed from relational algebra (e.g., Filter, Map, Union) and others are adapted to operate over continuous data streams (e.g., Aggregate, Join) [3]. The latter execute based on their bounded views, called *windows*, over the data streams to cope with the infinite nature of streams.

In a DSPS, the stream operators are distributed over multiple servers in a scalable manner [10, 22, 26]. We call the mapping between the operators and the servers that execute them a *query deployment plan*. Formally, given a set of servers $\{S_i\}_{i=1}^{n}$ and a query network Q (i.e., the union of all queries submitted), we denote a query deployment plan with $\{Q_i\}_{i=1}^{n}$, where each Q_i represents the set of operators that server S_i runs. We call Q_i the query on server S_i.

2.2 Previous HA Solutions for Stream Processing

Recently, a few HA techniques have been proposed for stream processing [21, 14, 5]. In those techniques, some prechosen servers (called *primary* servers) run queries and other servers act as *backup* servers. Each backup server is responsible for detecting the failure of its primary and, when the primary fails, immediately taking over the primary's execution. It is easy to see that these approaches provide significantly faster recovery than traditional log-based "restart recovery" techniques [18].

Stream-oriented HA solutions primarily differ in how the backup servers operate. Our previous paper [14] proposed the following three alternatives. In *passive standby*, each primary periodically copies to its backup *only the changed part* in its state. We call this task *delta-checkpoint* (or shortly *checkpoint*). Unlike passive standby, *active standby* uses *redundant execution*, in which each backup also receives the input data (from upstream servers) and processes them in parallel with its primary. Finally, in *upstream backup*, each primary logs its output data while the backup server remains inactive. If a primary fails, the backup rebuilds the primary's state from scratch by processing a subset of tuples logged at upstream servers. Approaches in [21, 5] fall into the active standby model.

2.3 Choosing Checkpoint as the HA method

Each HA method mentioned in Section 2.2 has unique relative benefits in terms of network utilization, recovery speed, recovery semantics, and the effect on regular processing [14]. In this paper, we choose to focus on *checkpointing* (i.e., passive standby) as the underlying HA method. As we argue below, our choice is primarily due to the observation that checkpointing can be used to effectively address a larger set of workload and configurations than other alternatives.

First, we do not use replay-based techniques (i.e., upstream backup) as they would not effectively support operators with large windows. Second, we do not consider redundant parallel execution (i.e., active standby) because it is, in general, more expensive than checkpointing and therefore may not sustain under *high load* situations that checkpointing can tolerate. More specifically, redundant parallel execution requires the backup to consume the same amount of computing resources as the primary because otherwise the backup will fall more and more behind the primary and eventually will fail to provide fast recovery. In contrast, checkpointing incurs significantly less overhead as it copies only the *remaining result* of the processing since the last checkpoint. For example, checkpoint does not incorporate the values that were newly entered but removed from the internal structure (i.e., the state) of an operator and the queues that the operator either reads from or writes to (those queues are to hold tuples until the next operator processes them). Checkpointing can also ignore the values overwritten in the past (e.g., all previous summary values of an aggregate operator) as well as all the read-only and computational operations (e.g., finding all the input tuples that match the join predicate). In Section 8.3, we experimentally demonstrate this point. Checkpointing also has an advantage that it can easily handle *nondeterministic* operators, whereas the other techniques require complex solutions [14].

3 Our Backup Model

In contrast to the previous HA models, our model enables parallelizing recovery over multiple machines. We begin this section by stating the assumptions behind this model. Then, we describe the overall framework and the operation during both non-failure and failure periods.

3.1 Assumptions

System Configuration. We assume that servers are grouped into *clusters* (e.g., 5-20 nodes) and study how the servers in each cluster can cooperate to achieve HA.

Communication. We assume that servers in the same cluster are connected with a fast, reliable network (e.g., gigabit LAN). The communication protocol guarantees robust message delivery and preserves message ordering. We do not consider network failures that isolate server clusters [5].

Failure Model. We assume that all servers are subject to failure and a failed server stops functioning (i.e., fail-stop) whereas alive ones are always responsive. We also assume that a server failure is a rare event and thus aim at protection against *single* server failures. It is generally acknowledged that a *1-safety* guarantee is sufficient for most real-world applications [12].

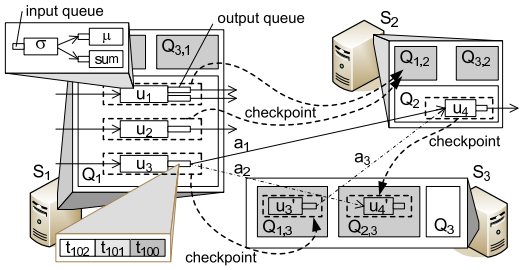


Figure 1. The Backup Model

Processing Load. We assume that the overall processing load is most of the time under the system's processing capability and well balanced over the servers (for this reason, each server can initiate HA tasks at idle times). We do not consider medium- to long-term overload situations because they in general necessitate load shedding [24] to favor timeliness over correctness, contradicting to the principle of HA.

3.2 The Basic Architecture

In this subsection, we describe the overall organization of the HA framework. We assume checkpoint as the means to maintain backups (refer to Section 2.3 for the reasons) and use Figure 1 for illustration. Once the system launches the query network, the query on each server can be viewed as a set of connected subgraphs. E.g., on server S_1, a Filter (σ), a Map (μ) and an Aggregate (sum) form a subgraph u_1. We take such a *maximal connected subgraph* as an *atomic unit* for checkpoint because checkpointing only part of it would yield an inconsistent backup image. E.g., for a chain that operator o_1 outputs to o_2, checkpointing only o_1 will leave (on the backup server) the image that would result from an invalid execution where some recent output of o_1 disappears while not being fed into o_2. For this reason, we call such a subgraph an *HA unit* and hereafter specify the query deployment plan in terms of such units. E.g., $Q_1 = \{u_1, u_2, u_3\}$, $Q_2 = \{u_4\}$, and so forth. Operators that belong to an HA unit are called *constituent operators*.

We also regard HA units on the same server as *independent* units for checkpoint (i.e., can be checkpointed onto *different servers* at *different times*) because they have no interdependency with each other (the benefits of such distribution are presented in Section 1). We call the mapping between HA units and their backup servers *backup assignment* and use $\{Q_{i,j} : i \neq j, 1 \leq i, j \leq n\}$ to represent it, where $Q_{i,j}$ is the set of HA units that server S_i executes and server S_j backs up ($i \neq j$ implies that a server cannot back up itself). We call each $Q_{i,j}$ an *HA segment*. In Figure 1, $Q_{1,2} = \{u_1, u_2\}$, $Q_{1,3} = \{u_3\}$, and $Q_{2,3} = \{u_4\}$. u_3' and u_4' are the backup images built by checkpointing u_3 and u_4 onto S_3, respectively. Each shaded area $Q_{i,j}$ represents the collection of backup images that S_j maintains for S_i.

It should be noted that the formation of HA units will significantly affect the behavior of the HA framework. We discuss this issue in Section 4.

3.3 No Loss Guarantee

In this paper, we provide *no data loss* guarantee. We however do not consider duplicate results that might appear during recovery because they can be eliminated in a straightforward manner [14].

To successfully mask a server failure, other servers in the cluster must be able to rebuild the latest state of the failed server. For example, if S_2 fails, the processing that involves u_4 no longer continues (i.e., stream a_1 does not flow). In this case, S_3 has to take over the blocked processing as it is the only one that owns the backup image u_4' of u_4. In more detail, S_3 has to set up a new connection a_2 to feed its backup image u_4' and start executing u_4' to recover the state of u_4. To prevent data loss in this case, each backup image must be able to obtain the tuples that the primary has processed since the last checkpoint. For example, if S_2 processed tuple t_{100} after checkpointing u_4 onto S_3, u_4' on S_3 must be able to receive that tuple through a_2. For this reason, each HA unit has *output queues*, one for each output, to retain such tuples (i.e., those that the downstream backups are currently missing). Those tuples can be safely discarded when the downstream server processes them and checkpoints the effect onto the backup server.

3.4 Non-Failure Time Operation for HA

As stated in section 3.1, we assume that each server has spare CPU cycles and uses them for HA purposes. An idle server can perform one of the following HA tasks:

- **Capture:** A server chooses an HA unit and sends (to the backup server for the HA unit) a message that captures the result of execution that the unit has done since the last checkpoint. We use the terms *capture* and *checkpoint message* to refer to, respectively, the task and the message that the task composes.
- **Paste:** A server chooses one among the checkpoint messages that it received, and copies the content of the message to the corresponding backup image that it maintains. We call this task *paste*. Once a paste finishes, the server notifies this to the sender of the message to enable the next round of checkpoint.

The rest of this section describes these tasks in detail. We defer the discussion on how they are scheduled to Section 5.

Contents of a Checkpoint Message. Because each capture begins at an idle time, the input queues of the HA unit (i.e., those of the constituent operators) at that time are always empty. For this reason, the checkpoint message ignores input queues and captures only the *constituent operators* (discussed in Section 7) and *output queues*. It should be noted that only a small part of each output queue needs to be captured. E.g., if S_2 acknowledged to S_1 the reception of t_{101}, then S_1 needs to copy only t_{102} to the output queue of u_3' on S_3. Note that only t_{102} is what a_3 will need if S_1 fails.

Checkpoint vs. Processing. Once a capture task begins, the server defers stream processing (i.e., only buffers arriving input tuples) until the capture ends. This is because (1) executing an HA unit while it is being captured might introduce inconsistency in the captured image (i.e., capture and processing conflict semantically) and (2) interrupting (i.e., slowing down) a capture to execute other HA units will further suspend the HA unit currently being captured (i.e., the HA unit will have an unfairly higher latency than others). If an exceptional input burst appears during a capture, it may be desirable to abort the ongoing capture and resume the processing to bound the growth of the latency. However, such an

abortion is not always useful because the change in the state tends to grow over time (i.e., a later capture is likely to be more expensive). In contrast to capture, paste (i.e., copying the content of a checkpoint message to the backup image) does not semantically conflict with processing and thus can be interleaved safely with processing.

Once a capture finishes, a *processing burst* appears until the deferred input tuples are consumed. Conceptually, the duration of capture implies the penalty of HA (i.e., the additional processing latency; we discuss this issue with the formation of HA units in Section 4) and both the capture cost and the server's processing load affect the duration of processing burst and in turn the checkpoint interval as well. In practice, we can set a lower bound on the checkpoint interval to prevent checkpointing too frequently (i.e., to trade off processing against HA). We can also set an upper bound that forces a checkpoint, bounding the growth of recovery time (i.e., trading off HA against processing).

3.5 Failure and Recovery

In our HA model, each server periodically pings other servers (every 100ms in our prototype). If a server does not react for a timeout period (300ms in our prototype), it is assumed to have failed (Section 3.1). When a server detects a failure in this manner, it first checks what HA units it has been backing up for the failed server. Then, it searches for *pending* checkpoint messages that the failed server has sent (i.e., those not yet consumed) and pastes them to the corresponding backup images. The server then begins executing the backup images as its new HA units, while redirecting the input and output streams (Section 3.3). We use the term *recovery* to refer to the process during which the alive servers in the cluster take these actions. When the servers collectively rebuild the latest state of the failed server, we say that the cluster has *recovered* from the failure. Note that *having recovered* does not necessarily imply *being able to mask the next failure*. This is because the system may not be able to tolerate the next failure until it secures, again by use of checkpoint, the HA units taken over during recovery. The *Period of instability* refers to the amount of time, after failure, until all HA units are again protected.

4 Formation of HA Units

As illustrated in Section 3.2, query deployment determines the formation of HA units and the behavior of our HA framework as well. In this paper, we take the position that the queries are deployed in a manner that best distributes the processing load over the machines [10, 22, 26, 25]. We start this section by showing that the load management principles for stream processing are even contributive to our HA framework. We then introduce a strategy that avoids having too many HA units to handle. Finally, we discuss preserving the safety guarantee while the system reforms HA units.

4.1 Impact of Load Management Principles

One principle of load management in stream processing is to distribute, over different machines, operators with highly correlated loads [26]. This is because placing them on the same machine will make it more vulnerable to load spikes. Adjacent operators (i.e., those connected by streams) usually exhibit high load correlation and therefore they (except those with very low processing load) are likely to be placed at different servers. Furthermore, operators with heavy computation are usually split into smaller pieces and distributed over multiple servers [10, 22] due to their negative impact on load management (refer to [25] for quantitative analysis). For the two reasons above, each server is likely to own many small-size operator chains (i.e., many fine-grained HA units).

Such load management policies are indeed advantageous in our HA model's perspective because (1) more HA units in general lead to better backup distribution (see Section 1 for the benefits) and (2) finer HA units tend to have smaller capture costs (i.e., smaller disruption in processing). Note that HA units with high capture costs can also be split in order to lower the costs.

4.2 Merging HA Units

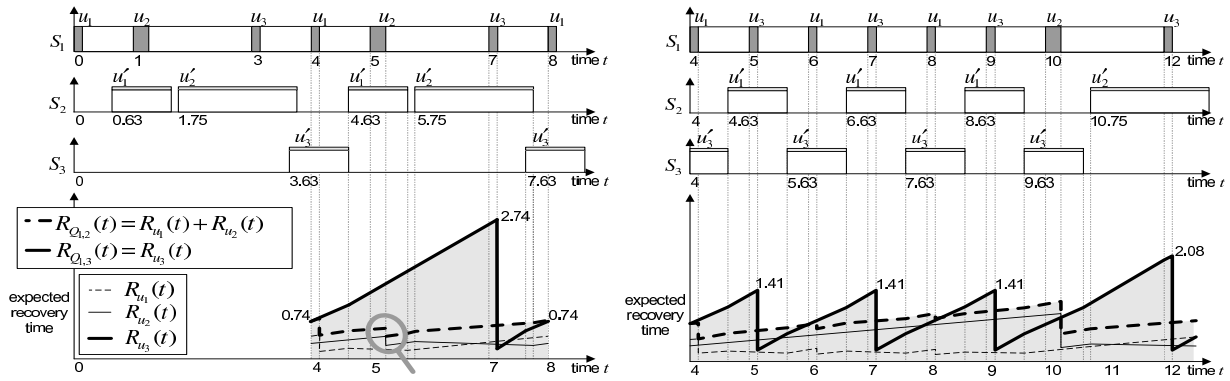
As discussed in Section 4.1, while having more HA units is usually beneficial in terms of backup distribution, having too many HA units may incur significant management overhead. We address this problem by iteratively *merging* HA units with similar characteristics (i.e., put all the operators that constitute those HA units into a new HA unit, even though they do not form a connected graph) as long as the capture cost remains under a threshold (say 0.5 second). As the similarity metric, we use the ratio of *processing load* over *capture cost* as this is what our checkpoint scheduler uses to optimize the recovery speed (Section 5). Merging HA units that are similar in this manner avoids making bad scheduling decisions because the merged HA units will get checkpointed with a similar frequency as before the merge.

4.3 Safety during HA Unit Reformation

Safety against failure has to be preserved even while the system reforms HA units due to operator splitting and migration. We achieve this by keeping the old backup images of the involved HA units, until the reformation completes and the newly formed HA units are again secured by backups. Due to page limitation, we cover only the following representative case. Suppose that an operator ρ is migrated to server S_i and added (as a constituent operator) to an HA unit u on S_i. In this case, the previous backup server S'_j for ρ has to keep its backup image ρ' of ρ until S_i checkpoints the expanded version of u onto the backup server for u (say S_j). This is because, before the checkpoint, S'_j is the only one that backs up ρ. S'_j can safely remove its backup image ρ' after S_j receives the checkpoint message that contains the image of ρ.

5 Checkpoint Scheduling

In our backup model, an idle server can perform either a *capture* task (i.e., among the HA units not being checkpointed, choose one, compose a checkpoint message for that one, and send the message to the right backup server) or a *paste* task (i.e., among the checkpoint messages received, choose one and copy the content of the message to the right backup image). In this section, we devise an algorithm that schedules such tasks in a manner that minimizes the expected recovery time. We first discuss how we can find the capture task that will most reduce the expected recovery time. Then, we describe how we choose the best from both capture and



(a) Round-Robin (b) Min-Max

Figure 2. Recovery Time (Round-Robin vs Min-Max)

paste tasks. We end this section discussing the key properties of our scheduling algorithm.

5.1 Choosing the Best Capture Task

When a capture ends, the primary server sends the backup server the changed part in the HA unit's state. Since the backup server then can efficiently freshen its backup image (by simply copying the change received), we can see that capturing an HA unit indeed expedites the recovery process. The recovery time however heavily depends on the checkpoint schedule.

Figure 2(a) shows an exemplary case where server S_1 checkpoints its HA units u_1 and u_2 onto S_2, and u_3 onto S_3 in a round-robin fashion. To ease illustration, we do not consider the paste tasks that S_1 would perform and the capture tasks that S_2 and S_3 would do. We assume that HA units on S_1 have constant processing loads (in terms of percentage of CPU cycles): $l_{u_1}(t) = 11\%$, $l_{u_2}(t) = 10\%$, and $l_{u_3}(t) = 66.5\%$ for all time t. We also assume that those units have (1) constant capture costs (in seconds): $c_{u_1}(t) = 0.125$, $c_{u_2}(t) = 0.25$, and $c_{u_3}(t) = 0.125$ for all time t and (2) the same paste costs as capture costs: $c'_{u_k}(t) = c_{u_k}(t)$ for $k = 1, 2, 3$. These assumptions are again to ease illustration. In Sections 8.1 and 8.2, we present the details in real cases.

As described in Section 3.4, each capture (represented as a dark rectangle in Figure 2) defers query processing and, for this reason, a processing burst (represented as an empty rectangle) appears after that. The duration of such a burst, as mentioned before, is a function of the capture cost and the server's processing load. E.g., the duration of the burst after capturing u_1 is $\frac{c_{u1}(t)\left(l_{u_1}(t)+l_{u_2}(t)+l_{u_3}(t)\right)}{1-\left(l_{u_1}(t)+l_{u_2}(t)+l_{u_3}(t)\right)} = \frac{0.125 \cdot 0.875}{1-0.875} = 0.875$ (second). The figure illustrates that each paste is deferred until its turn and, in contrast to captures, is interleaved with query processing (refer to Section 3.4 and the stacks of grey and empty rectangles in the figure).

Figure 2(a) also demonstrates how the expected recovery time changes over time for various entities such as HA units u_1, u_2, u_3, HA segments $Q_{1,2}$, $Q_{1,3}$ and the query Q_1 on server S_1. We use the convention that $R_*(t)$ represents the expected amount of time to recover an entity $*$ if the primary server for $*$ fails at time t (due to page limitation, we leave the formal definitions in [15]). The figure shows that capturing u_2 during $[5, 5.25]$ reduces $R_{u_2}(t)$ from 0.43 to 0.28 when it finishes at 5.25. The reasons are as follows: (1) when the capture is about to end, the backup image u'_2 on S_2 has the state of u_2 as of time 1 and thus the expected amount of time to recover u_2 is $\int_1^{5.25} l_{u_2}(\tau)d\tau = 0.43$ (second); (2) after the capture finishes, S_2 will take, if S_1 fails, $c'_{u_2}(t) = 0.25$ second to consume the checkpoint message and $\int_5^{5.25} l_{u_2}(\tau)d\tau \simeq 0.03$ second to replay the recent execution of u_2 on S_1. That capture task for u_2 also reduces $R_{Q_{1,2}}(t)$ (i.e., the time that S_2 will take to recover all the HA units that it backed up for S_1) by the same amount (note that $R_{Q_{1,2}}(t) = R_{u_1}(t) + R_{u_2}(t)$). However, the capture task *fails to reduce* $R_{Q_1}(t)$. This is because (1) the system recovers from S_1's failure only if both S_2 and S_3 recover their backup segments $Q_{1,2}$ and $Q_{1,3}$, respectively (i.e., $R_{Q_1}(t) = \max\{R_{Q_{1,2}}(t), R_{Q_{1,3}}(t)\}$) and (2) capturing $u_2 \in Q_{1,2}$ does not relieve the largest recovery load on S_3 (note that $R_{Q_{1,3}}(t) > R_{Q_{1,2}}(t)$). *To reduce $R_{Q_1}(t)$, S_1 at time 5 should have started capturing $u_3 \in Q_{1,3}$ rather than $u_2 \in Q_{1,2}$.*

Based on this observation, we design an algorithm that selects an HA task that *will minimize the maximum recovery load* among those spread over other servers (for this reason, we call our scheduling algorithm "*min-max*"). In detail, each server S_i looks for all HA unit $u \in Q_{i,j}$ such that (1) $u \in$ `c-q` and (2) $R_{Q_{i,j}}(t + c_u(t)) = R_{Q_i}(t + c_u(t))$, where `c-q` is a queue that remembers the HA units that S_i can checkpoint immediately (i.e., those not being checkpointed) and $t + c_u(t)$ is the time when capturing u will end. Note that condition (2) implies that u's backup server S_j will have *the maximum recovery load when capturing u is about to finish.* Among such HA units, the server finds the HA unit u^* such that capturing it will *most efficiently reduce the recovery time*. As the metric for this, the server uses $\frac{\Delta R_u(t)}{c_u(t)}$ for each HA unit u, where $\Delta R_u(t)$ denotes the reduction in recovery time at the cost $c_u(t)$ of capturing u. We define $\Delta R_u(t)$ as $\int_{\alpha_u(t)}^{t} l_u(\tau)d\tau - c'_u(t)$, where $\alpha_u(t)$ denotes the start time of the previous capture (the first and second terms represent the *gain* of freshening the backup image and the *penalty* of consuming the checkpoint message, respectively). Notice that this discipline prefers HA units with *high processing load* (see $l_u(\tau)$ in the numerator of the metric) and *low checkpointing cost* (see $c_u(t)$ and $c'_u(t)$ in the metric).

Whenever S_i forms an HA unit $u \in Q_{i,j}$
01. c-q.push(u, i); // enqueue the HA unit
Whenever Idle
02. $\mathcal{C} \leftarrow \{(u,j) \in$ c-q $: R_{Q_{i,j}}(t + c_u(t)) = R_{Q_i}(t + c_u(t))\}$
03. find $(u^*, j^*) \in \mathcal{C}$ such that // find the best HA unit to capture
$\frac{\Delta R_{u^*}(t)}{c_{u^*}(t)} = \max\{\frac{\Delta R_u(t)}{c_u(t)} : (u,j) \in \mathcal{C}\}$
04. for each j $(1 \le j \le n,\ j \ne i)$
05. $(u, \Delta) \leftarrow$ p-q[j].first() // oldest checkpoint msg from S_j
06. if $\left(R_{Q_{j,i}}(u,t) > R_{Q_{i,j^*}}(u^*,t)\right)$
07. if $\left(u' =$ null $|| R_{Q_{j,i}}(u,t) > R_{Q_{j',i}}(u',t)\right)$
// if no best paste so far or the current one is the best
08. $(u', j', \Delta') \leftarrow (u, j, \Delta)$ // remember the best paste
09. if ($u' =$ null) // if no paste is better than the best capture
10. capture(u^*, j^*); // do the best capture
11. remove (u^*, j^*) from c-q;
12. else // if there exists a paste better than the best capture
13. paste(u', j', Δ') // do the best paste
14. remove (u', Δ') from p-q[j'];
capture(u^*, j^*)
15. copies into Δ the recent change in u^*;
16. S_{j^*}.p-q[i].push(u^*, Δ);
paste(u', j', Δ')
17. copies Δ' into u';
18. $S_{j'}$.c-q.push(u, i);

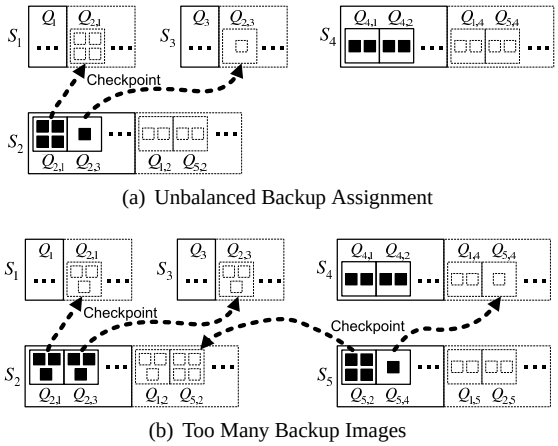
Figure 3. Min-Max Scheduling (on server S_i)

5.2 Capture vs Paste

In principle, a server conducts *capture tasks* to better prepare for the failure of itself and *paste tasks* for the failure of others. To strike a balance between these goals, each server finds the HA task, no matter it is a capture or a paste, that will assist the HA segment with the largest recovery load. In detail, server S_i first computes $R_{Q_{i,j^*}}(u^*, t)$, the expected recovery time for the moment when it finishes capturing the best HA unit $u^* \in Q_{i,j^*}$ (we formally define this in [15]). Then, for each backup segment $Q_{j,i}$, it computes the expected recovery time for the moment when it completely consumes the *oldest pending* checkpoint message from S_j (this FIFO order is to obey the decisions that S_j made). Using $u \in Q_{j,i}$ to denote the HA unit that the checkpoint message was for, we represent such expected recovery time as $R_{Q_{j,i}}(u,t)$ (again see [15] for the formal definition). If $R_{Q_{j,i}}(u,t) > R_{Q_{i,j^*}}(u^*,t)$, it assumes that backup segment $Q_{j,i}$ needs more care than primary segment Q_{i,j^*} (i.e., the paste for $u \in Q_{j,i}$ is more urgent). The server selects the best from capture and paste tasks based on this rationale.

5.3 The Complete Scheduling Algorithm

Figure 3 summarizes the min-max algorithm. Whenever a server forms a new HA unit, it pushes it into c-q (line 01). An idle server first finds the best capture task (lines 02-03) and attempts to find the paste task that is more effective than all others (including the best capture task) (lines 04-08). Finally, it performs the best task found. If a capture task is chosen (lines 09-11), the server composes a checkpoint message and sends it to the relevant backup server (lines 15-16). If a paste task is chosen (lines 12-14), the server consumes the checkpoint message and then notifies the completion of checkpoint to the primary (lines 17-18).



(a) Unbalanced Backup Assignment

(b) Too Many Backup Images

Figure 4. Backup Reassignment

5.4 Discussion

Our min-max algorithm selects the HA task that will most reduce the largest recovery load. Figure 2 shows an example where such a scheduling discipline maintains the recovery time at a 30% lower level than round-robin (in Section 8, we show the results in real cases). The figure also shows that min-max takes a longer time than round-robin until it checkpoints each HA unit at least once (we call such a period of time a *checkpoint cycle*). This is because min-max frequently checkpoints HA units with high processing load and low checkpoint cost, yielding a non-uniform schedule. The figure also shows that the recovery time under min-max gradually increases until it drops at the end of a checkpoint cycle. This is because the backup images of uncheckpointed HA units get staler over time.

6 Dynamic Backup Assignment

In our HA model, the recovery time depends on not only in what schedule the system takes checkpoints, but also in what manner it assigns the backup servers. For example, a server with high backup load will easily be the system bottleneck that delays the circulation of HA tasks. If this happens, other servers in the cluster will not be able to efficiently use spare CPU cycles for HA and therefore the system will be poorly prepared for failure. In this section, we study how we can avoid this problem. We assume that servers with low backup load volunteer to back up new HA units whenever they appear. Hereafter, we focus on modifying the backup assignment to cope with varying system conditions introduced by operator migration, changes in input rates, etc.

6.1 Determining Backup Load Imbalance

In principle, our algorithm reassigns backups to assist the server whose failure will have the most negative impact (i.e, the one the failure of which will cause the longest recovery). We call such a server *the worst point of failure*. We adopt such discipline because a server usually becomes the worst point of failure due to unbalanced backup distribution and it is always advantageous to improve the worst-case disruption that a failure might cause. We use Figure 4 to illustrate two typical cases of backup imbalance. We assume that S_2 is the worst point of failure and, to ease presentation, all the HA

On server $S_{\bar{i}}$ with the highest recovery time, whenever epoch E ends

01. Find $\underline{k}, \overline{j}, \underline{j}$ such that
$R_{Q_{\bar{i},\overline{j}}}(E) = \max_{j=1}^{n} R_{Q_{\bar{i},j}}(E)$
$R_{Q_{\bar{i},\underline{j}}}(E) = \min_{j=1}^{n} R_{Q_{\bar{i},j}}(E)$
$R_{Q_{\underline{k}}}(E) = \min_{k=1}^{n} R_{Q_k}(E)$
02. if $R_{Q_{\bar{i},\underline{j}}}(E) < R_{Q_{\underline{k}}}(E)$ // if the backup load is unbalanced
03. move($\overline{j}, \underline{j}$) // balance the backup load
04. else // if $S_{\bar{i}}$ has too many backup images
05. find $\overline{k} = \arg\max_{k=1}^{n} \left[R_{Q_{k,\bar{i}}}(E) - R_{Q_{k,\underline{k}}}(E)\right]$
06. $S_{\overline{k}}$.move($\bar{i}, \underline{k}$) // let $S_{\overline{k}}$ balance the backup load

$S_{\bar{i}}$**.move(**$\overline{j}, \underline{j}$**)**

07. $\Delta h \leftarrow \frac{R_{\bar{i},\overline{j}}(E) - R_{\bar{i},\underline{j}}(E)}{R_{\bar{i},\overline{j}}(E)} h_{Q_{\bar{i},\overline{j}}}(E)$ // backup load to transfer
08. for each $u \in Q_{\bar{i},\overline{j}}$
09. if $h_u(E) \leq \Delta h$ // if finds an HA unit to reassign the backup
10. $\Delta h \leftarrow \Delta h - h_u(E)$ // update the backup load to move
11. $Q_{\bar{i},\overline{j}} \leftarrow Q_{\bar{i},\overline{j}} - \{u\}$ // reassign the backup server
12. $Q_{\bar{i},\underline{j}} \leftarrow Q_{\bar{i},\underline{j}} \cup \{u\}$

Figure 5. Backup Reassignment

units (i.e., those represented as dark small rectangles) have identical properties. Backup images are represented as small dotted-line rectangles. Figure 4(a) shows the case where S_2 has poorly assigned the backup servers (i.e., S_1 backs up too much for S_2). In the example, S_2 can resolve the problem by transferring part of S_1's backup responsibility to S_3 (i.e., S_3 will then back up some HA units that S_1 has been backing up). Figure 4(b) shows another case where S_2 maintains too many backup images for others. In this case, S_2 should not reassign backups as it cannot improve any further. Instead, a different server (say S_5) should do the task for S_2.

6.2 The Backup Reassignment Algorithm

Figure 5 summarizes our backup reassignment algorithm. At the end of *epoch* E (the period required for every server to finish at least one checkpoint cycle), the servers in the cluster determine the worst point of failure $S_{\bar{i}}$, based on the expected recovery times averaged over the epoch. We use this periodic approach because (1) it is hard to know the recovery time in an average sense before a checkpoint cycle ends (see Section 5.4) and (2) we should avoid changing backup assignment too frequently. Note that checkpointing an HA unit onto a new backup server (i.e., a whole checkpoint) is usually more expensive than an ordinary delta-checkpoint.

Server $S_{\bar{i}}$ (the worst point of failure) first finds its HA segments $Q_{\bar{i},\overline{j}}$ with the highest recovery load and $Q_{\bar{i},\underline{j}}$ with the lowest recovery load (note that $R_{Q_{\bar{i},\overline{j}}}(E) > R_{Q_{\bar{i},\underline{j}}}(E)$ by definition). It also finds another server $S_{\underline{k}}$ whose failure will result in the shortest recovery (line 01). If $R_{Q_{\bar{i},\underline{j}}}(E) < R_{Q_{\underline{k}}}(E)$, $S_{\bar{i}}$ assumes that $S_{\underline{j}}$ is assigned too low backup load and accordingly balances the backup load between $S_{\overline{j}}$ and $S_{\underline{j}}$ (lines 02-03; in Figure 4(a), $S_{\overline{j}}$ and $S_{\underline{j}}$ correspond to S_1 and S_3, respectively). Otherwise (line 04), it assumes that it has too many backup images and locates a different server $S_{\overline{k}}$ that will effectively balance the backup load between $S_{\bar{i}}$ and $S_{\underline{k}}$ (lines 05-06; in Figure 4(b), $S_{\overline{k}}$ corresponds to S_5. $S_{\bar{i}}$ and $S_{\underline{k}}$ correspond to S_2 and S_4, respectively).

The **move(**$\overline{j}, \underline{j}$**)** phase in Figure 5 shows the details of reassigning backup servers. In the algorithm, $h_u(E)$ denotes the total CPU cycles used for updating the backup image of HA unit u during epoch E (we call this the *backup load* of HA unit u). Similarly, $h_{Q_{\bar{i},j}}(E)$ represents the backup load of HA segment $Q_{\bar{i},j}$. To balance the backup load, $S_{\bar{i}}$ first computes the amount of backup load Δh to move from segment $Q_{\bar{i},\overline{j}}$ to segment $Q_{\bar{i},\underline{j}}$ (line 07). Then, it reassigns backup servers until the amount of backup load transferred reaches Δh (08-12). During this iteration, we can also prefer the HA units that will show minimal increase in checkpointing cost (i.e., those that the cost of whole-checkpointing them will least differ from that of delta-checkpointing them). Note that this **move** phase only chooses the new locations to put backup images. The first checkpoints after reassignment in fact create the backup images.

7 Delta Checkpointing

An efficient checkpointing mechanism will shorten the duration of HA tasks, implying better runtime performance (because the disruption in processing will decrease) and faster recovery speed (because more frequent checkpoints will be possible). In this section, we describe how to implement efficient, operator-specific delta-checkpointing techniques based on the details of operators. We also construct the associated cost models. In Section 8, we demonstrate that we can accurately estimate checkpoint costs and therefore the min-max scheduling hardly makes wrong decisions.

As described in Section 3.4, capturing an HA unit requires incorporating the states of the constituent operators and, for each output queue, a round trip worth of tuples. The latter however can be ignored safely by holding the checkpoint message until the downstream servers acknowledge the reception of them. Therefore, we can represent the cost $c_u(\alpha)$ of capturing an HA unit u as $\sum_{\rho \in u} c_\rho(\alpha)$, where α is the start time of the capture task and $c_\rho(\alpha)$ is the cost of capturing the internal data structure of a constituent operator ρ. Because stateless operators will not incur any checkpoint cost, we design (and analyze) the delta-checkpointing methods for only the two representative stateful operators, Aggregate and Join.

7.1 The Aggregate Operator

The Aggregate operator groups input stream I into substreams $\{I[g]\}$, one for each group-by value g. For each substream $I[g]$, it assumes windows (sets of tuples) of w seconds that appear every s seconds (we can also define windows in terms of tuple counts). Whenever a window expires, the operator outputs an aggregated value computed from the tuples contained in the window. In more detail, whenever an input tuple arrives, the operator (1) reads (from the tuple) timestamp t and group-by value g. Next, the operator (2) uses its "map" to quickly locate *the list of windows* associated with g (if none exists, it creates a new list), and (3) determines if it needs to add new windows (e.g, if the timestamp t of the tuple is 401.5 and the timestamp of the most recent window is 400, an Aggregate with step size s of 1 second will add a window anchored at time 401). Then, the operator (4) iterates over the windows in the list updating the summaries (e.g., counts, sums, or histograms, etc.) that those windows maintain. Finally, it (5) closes expired windows while send-

ing their summaries as output tuples.

Delta-Checkpointing. We use one dirty bit for each group-by value to mark those that have appeared since the last checkpoint (we clear all the dirty bits at the end of capture). We also use one dirty bit for each window to distinguish if it was updated after the last checkpoint. To capture an Aggregate, the primary server finds all the windows associated with group-by values with their dirty bits on and copies into the checkpoint message (1) the entire content of each window with its dirty bit off (*full capture* for new windows) and (2) only the summary of each window with its dirty bit on (*partial capture* for updated windows). When the backup server consumes the checkpoint message, it checks the captured window images in the message. For a full captured image, it creates a new window from the image and associates the window with the right group-by value (i.e., *full paste*). Otherwise, it copies the partial image onto the corresponding window that already exists in the operator (i.e., *partial paste*).

Cost Model. We can represent the cost of capturing this operator as $C_n c_f + C_u c_p$, where C_n is the number of windows created after the last checkpoint, C_u is the number of updated windows, and c_f and c_p are the costs of fully and partially capturing a window, respectively. We can similarly define the paste cost using per-window full/partial paste costs.

7.2 The Join Operator

The Join operator takes input streams I_1 and I_2. The operator searches for all pairs of input tuples (one from each input stream) that (1) belong to the same window of size w and (2) match the predicate defined for the operator. Whenever the operator finds such a pair of *matching input tuples*, it produces the concatenation of them as an output tuple.

Delta-Checkpointing. Since the recent change in state is the tuples newly entered the window, each checkpoint captures those tuples. It also captures the upper bound of the tuples that have left the window so that the backup server can remove those tuples from the backup state.

Cost Model. The number of tuples that have entered the window since the last checkpoint can be represented as $(\lambda_1 + \lambda_2) \min(t - \alpha, w)$, where t is the current time, α is the start time of the last checkpoint, and λ_1 and λ_2 are the input rates (i.e., the number of input tuples per second) of input streams I_1 and I_2, respectively. Therefore, the capture cost can be represented as $(\lambda_1 c_1 + \lambda_2 c_2) \min(t - \alpha, w)$, where c_1 and c_2 are the cost of capturing one tuple obtained from input streams I_1 and I_2, respectively. We can similarly define the paste cost.

8 Experimental Results

In this section, we describe experimental results using both our Borealis DSPS [7, 3, 5, 2, 26, 14] and a detailed simulator. First, we describe how we set up the experiments (Section 8.1). Then, based on the results from the prototype, we investigate how the cost of checkpointing varies depending on the frequency of checkpoints (Section 8.2). We also demonstrate how our technique effectively reduces the recovery time while being minimally intrusive to regular query processing (Section 8.3). Finally, we present supplementary results obtained from the simulator (Section 8.4).

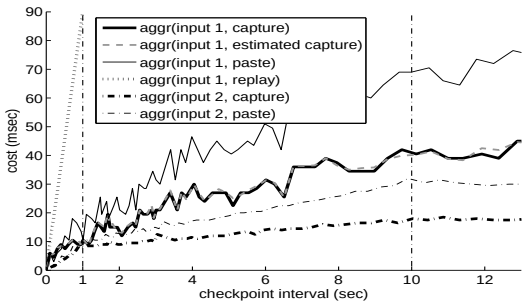


Figure 6. Analysing Checkpointing Costs

8.1 The Setup

In our experiments, we used a five server cluster where a 1GBps router interconnets servers with a AMD Sempron 2800+ CPU and 1GB main memory. We used two different input streams. The first (Type 1) is a wide-area TCP trace obtained from [1]. We extract the timestamp and the source-IP address from each packet to form an input feed that runs at 2.0K tuples/sec on average. As commonly observed, the trace has a widely varying stream rate (std = 0.7K tuples/sec) and its source-IP addresses have a highly skewed distribution. The second (Type 2) is an artificial input stream with a source-IP-address field that ranges uniformly from 0 to 99, with a constant input rate of 100 tuples/sec. These two input streams were designed to represent dissimilar loads.

Our test query uses aggregate operators with a window size of 10 seconds and step size of 1 second. These operators also group tuples by the source-IP address. We used aggregates for generality since they are commonly implemented as described in Section 7.1 and therefore exhibit representative behavior in terms of both processing and checkpoint costs (whereas join implementations vary drastically). We form an HA unit for two parallel aggregates fed by a single input stream. On each server, we generate four HA units with input type 1 and another four HA units with input type 2.

8.2 Checkpointing Costs

In this experiment, we vary the frequency of checkpoints and observe how the cost of checkpointing an aggregate operator varies on both primary and backup (Figure 6). As expected, when the checkpoint frequency decreases (i.e., the interval increases), both the time to form a checkpoint (capture cost) and the time to consume a checkpoint (paste cost) increase. This is because the state of the primary will increasingly diverge from the state of the previous checkpoint. Notice that the curves for the type 1 aggregate have jitters, showing how much the checkpoint cost may vary each time due to the burstiness of real packet streams. The figure also shows that type 1 aggregate has a *relatively lower checkpoint cost* than type 2 aggregate (considering its significantly *higher processing load* due to 20 times faster input rate). This is because the former maintains relatively fewer windows because of the skewed distribution of group-by values.

The curve for aggr(input 1, estimated capture) shows that we can quite accurately estimate the checkpoint cost; this is important because the min-max algorithm operates on the basis of cost estimations. In this case, we estimated the per-

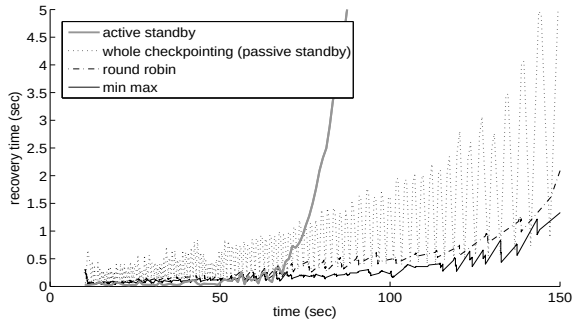


Figure 7. Recovery Time

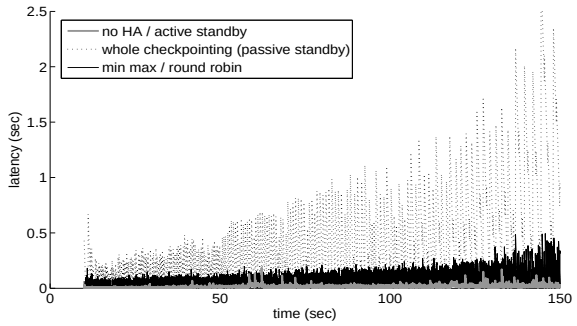


Figure 8. End-to-End Processsing Latency

window full/partial capture costs (in μsecs) as c_f=18.6 and c_p=7.3 (see Section 7.1) using linear regression over the collection of triples [# new windows (C_n), # updated windows (C_u), capture cost ($C_n c_f + C_u c_p$)]. Paste costs can also be estimated with per-window paste costs as c'_f=30.2 and c'_p=7.2.

The figure also shows the bounded nature of the operator states: all curves tend to plateau after a 10 second checkpoint interval mainly because the operator can contain at most a 10-second worth of tuples. The curves for the type 2 aggregate flatten out after a 1-second interval, as its input creates at most 100 group-by values. The gradual increase of those curves between 1 and 10 seconds accounts for the increase of new windows created after the previous checkpoint. Note that the type 1 aggregate does not show such flattening (as it continually observes new IP-addresses) until the checkpoint interval surpasses the window size. The figure also shows that paste costs are usually higher than capture costs due to the allocation of new windows (observe $c'_f > c_f$).

Finally, the difference between (input1, replay) and (input 1, paste) shows the benefit of checkpointing over the execution-based backup method (i.e., active standby). In particular, (input1, replay) shows how long it has to execute until it makes "up to date" the same stale backup image used in the corresponding checkpoint case. Checkpointing uses much fewer CPU cycles due to the reasons described in Section 2.3 and the bounded nature of operators as argued above.

8.3 Recovery Time and End-to-End Latency

In this experiment, we study how the *expected recovery time* and *end-to-end latency* change (due to HA tasks) as we increase the stream rate of input type 1 from 0 to 2.0K tuples/sec in our prototype implementation. As before, input type 2 maintains a stream rate of 100 tuples/sec. We deployed

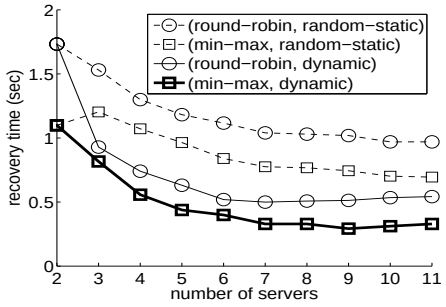


Figure 9. Scheduling & Backup Assignment Effects

the same query network on each of the five homogenous servers. Then, we formed one HA unit for the whole checkpointing case and 8 HA units (as described in Section 8.1) for all other cases. The HA units were uniformly assigned backup servers to avoid imbalance in backup load.

Figure 7 shows how the expected recovery time changes as the input rate increases. We can see that active standby cannot sustain as the overall processing load increases beyond 50% of the cluster's computation capability. This is not surprising since backup processing requires the same amount of resources as primary processing. In contrast, checkpoint-based methods continue their operations while both round robin and min max exhibit significantly faster recovery speed than whole checkpointing due to the distribution of recovery load over multiple servers. Min-max enables the shortest recovery by favoring Type 1 HA units over Type 2 HA units.

Figure 8 shows how the HA tasks affect query processing. We do not present the curve for active standby as its latency is similar to the latency without any HA method. Notice that, to be fair, we assumed a distributed adaptation of the basic active standby model that can flexibly trade off processing against HA under overload situations. The figure also shows that fine grained checkpoint techniques disrupt regular processing much less than the standard whole checkpointing approach (round robin behaves similar to min max).

8.4 Scheduling and Backup Assignment

Figure 9 shows how recovery time changes as we increase the number of servers for combinations of scheduling algorithms (round-robin and min-max) and backup assignment techniques (random-static and dynamic). This result was obtained from our detailed Borealis simulator. Round-robin scheduling and random-static assignment are considered to be the baseline cases. We compare the more robust algorithms, min-max and dynamic, with the baseline.

The first thing to notice is that since we only assign eight HA units to each primary server, the recovery time does not improve as the number of servers increases past nine. At nine, each HA unit can be backed up on its own server. When we fix the scheduling policy, the difference between the random-static placement and dynamic placement is significant, yielding approximately 50% improvement in recovery time. This demonstrates the penalty of a random distribution in that such a distribution will not be balanced in general, and the overall recovery time is bounded by the worst case

recovery time across all servers. Moreover, the scheduling algorithm can do better in assigning a checkpoint frequency when the backup servers are well balanced. This has the effect of also reducing recovery time as the checkpoint intervals will get smaller. Notice that min-max improves recovery time by only 25% with random-static, whereas it improves recovery time by 50% with dynamic. Further results on the impact of the processing load as well as the differences in operators can be found in [15].

9 Related Work

Providing high availability through checkpointing has been widely studied in distributed systems. Most approaches rely on stable storage that survives failures [9]. Early approaches conduct coordinated checkpoints so that the stable storage always has a system-wide consistent state [9, 11]. There have been also alternative approaches that combine asynchronous checkpointing with logging of non-deterministic events [6, 23]. In principle, our approach builds, for each server, a virtual, distributed backup storage on other servers. To maintain this storage, it uses asynchronous, fine-grained checkpoints that are optimized for stream processing.

Modern DBMSs often protect data from server failures by replicating data from a source database, called the primary, to a target database, called the standby. IBM DB2 HADR (High Availability Disaster Recovery) [16], Oracle 10g/DataGuard [20] and MS SQL 2005's Database Mirroring [19] all adopt this style of replication. Workflow systems such as IBM WebSphere MQ [17, 13] also mask server failures by using standby machines. These solutions usually store message logs on a remote site, so that both the primary and standby machines can access them. In contrast to those conventional systems, our solution maintains the backup in a distributed, self-configuring manner and also effectively uses spare CPU cycles to improve system availability.

In the context of our target stream processing domain, a few recent work addressed high availability and related issues (we also discuss them in Sections 2.2 and 3.1). The approaches presented in [21] and [5] rely on "active" HA models in which the backup servers also actively process queries in parallel with the primaries. These active approaches usually have better failover performance, while trading off their query processing capability (note that the backup processes in this case must use the same amount of system resources as the primary processes). We presented a checkpoint-based approach in [14]. Our previos work does not consider cooperative backup and recovery and, therefore, also does not address many of the related challenges (and opportunities).

10 Conclusion

This paper considers a novel checkpoint-based HA solution that addresses the needs of distributed stream processing through a parallel fine-grained backup and recovery approach that incurs lower overhead and yields shorter recovery times than existing ones. The key idea is to sub-divide the query at a given server into units that can each be backed-up on a different server. The approach has the advantage that each unit can be checkpointed separately and independently, thereby spreading out the checkpoint burden over time. It also reduces the overall recovery time because each unit can be rebuilt in parallel, making the total recovery time equal to the recovery time of the slowest backup piece. Our design schedules backups in a way that is least disruptive to normal processing.

In this context, we studied how to distribute the backup load in order to minimize the expected recovery time. We also showed how our min-max algorithm adapts to changes in system processing load and performs significantly better than more standard approaches.

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