Falkirk Wheel: Rollback Recovery for Dataflow Systems

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Abstract

We present a new model for rollback recovery in distributed dataflow systems. We explain existing rollback schemes by assigning a logical time to each event such as a message delivery. If some processors fail during an execution, the system rolls back by selecting a set of logical times for each processor. The effect of events at times within the set is retained or restored from saved state, while the effect of other events is undone and re-executed. We show that, by adopting different logical time "domains" at different processors, an application can adopt appropriate checkpointing schemes for different parts of its computation. We illustrate with an example of an application that combines batch processing with low-latency streaming updates. We show rules, and an algorithm, to determine a globally consistent state for rollback in a system that uses multiple logical time domains. We also introduce *selective rollback* at a processor, which can selectively preserve the effect of events at some logical times and not others, independent of the original order of execution of those events. Selective rollback permits new checkpointing policies that are particularly well suited to iterative streaming algorithms. We report on an implementation of our new framework in the context of the Naiad system.

1 Introduction

This paper is about fault tolerance in distributed dataflow systems. Specifically, we investigate the information that must be tracked and persisted in order to restart a system in a consistent state after the failure of one or more processes. We assume other requirements, such as detecting failures and reliably persisting state, are adequately covered by existing techniques. We describe a general mechanism and an implementation of it in the context of the Naiad [12] system. We also suggest how the ideas may be applied to other distributed systems. The mechanism is named after the Falkirk Wheel [2], a prior engineering solution for high-throughput streaming rollback.

Most fault-tolerant distributed systems adopt a fixed policy for checkpointing and logging. As a result, all applications running on these systems must operate with the same set of performance tradeoffs. Streaming applications often require high availability, i.e. the system must resume output soon after the detection of a failure. Systems designed for these applications must be able to restore quickly to a recent consistent state on failure, meaning they must frequently update persistent state. Other applications may be more sensitive to throughput or latency, which are hard to maintain while eagerly writing to stable storage. These conflicting application requirements are a major motivation for the development of multiple systems such as Spark [13], Storm [5], S4 [4] and Millwheel [6]. We argue that such systems would be more useful if they could mix policies, and thus performance tradeoffs, within a single application.

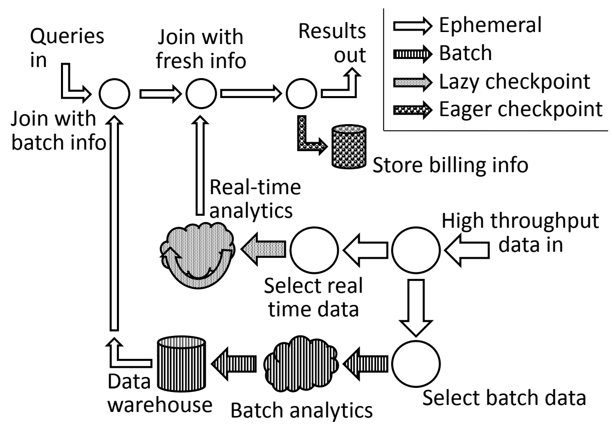


Figure 1: A complex streaming application. Different parts of the computation have different availability, throughput and latency requirements, and thus merit different fault-tolerance policies.

Consider the application in Figure 1. User queries arrive at the top left and are joined with two sets of data: the output of a periodic batch computation; then the output of a continuously-updated iterative computation. Statistics about the query response are then stored in a database and the response is delivered back to the user. Concurrently the application receives a high-throughput stream of data records. Some fields of these records are directed to the batch computation, which is re-run periodically. Other fields are used as inputs to the iterative computation which updates in real time.

The application adopts four separate fault-tolerance regimes for different regions of the computation, indicated by the different shading used for different parts of the dataflow illustration. The first we call "ephemeral" which means that the records flowing through this part of the graph are never saved to stable storage, and none of the dataflow vertices they pass through store mutable state. Clients that introduce ephemeral records (users sending queries or the external service supplying high-throughput data) do not receive an acknowledgement until the records have flowed through the entire ephemeral subgraph, so fault tolerance for these records is attained by requiring clients to retry on failure. Data reductions are performed on the high-throughput input records before they leave the ephemeral regime. The second regime is "batch." In this part of the graph there is a high-throughput data-intensive computation that is run periodically and can tolerate re-execution that introduces a high increase in latency (perhaps of minutes) in the case of a failure, since the results of the computation are never required to be fresh. The third regime is "lazy checkpoint." This is used for the real-time analytics subgraph which maintains complex state that must be regularly checkpointed. In the event of a failure it is acceptable to re-execute a few seconds' worth of work in this regime, so checkpoints need not be taken every time state is updated. The final regime is "eager checkpoint." This is used for the database updates which must be persisted as soon as they are recorded, since they must be consistent with delivered results. There exist fault tolerance designs that fit several of these regimes, but no current system can include them all in a single application as we desire. The Falkirk Wheel framework makes this flexible mixture of policies possible.

In common with prior work [9] we propose to recover from a failure by restoring processes to previously-checkpointed states, optionally replaying logged events such as message deliveries that occurred after the checkpoints were taken, then restarting execution. Many standard checkpointing and logging techniques can be understood in terms of events tagged with partially-ordered *logical times*. After a failure the effect of events at logical times in a chosen set is restored from saved state, and events with times outside the set are re-executed. This paper makes two major contributions. First, we show how different subgraphs of a dataflow can make use of different logical time *domains*. This permits different styles of checkpointing, with different performance tradeoffs, to coexist within a single fault-tolerant application. We set down simple rules and a general algorithm for choosing a consistent global state after a failure, taking into account these different time domains. Second, we introduce the concept of *selective rollback*. This means that a process that has processed events at two different logical times t_1 and t_2 may be able to preserve the work for time t_1 after rollback but undo and re-execute the work for t_2, independent of the order in which the work was originally performed. We show that selective rollback allows new performance tradeoffs that are particularly well-suited to high-throughput, low-latency systems such as Naiad.

Our implementation targets the Naiad system, which previously had only basic support for fault tolerance. Naiad adopts a single underlying system mechanism and implements different computational models as libraries. Our design allows each library to adopt a checkpointing policy tailored to its performance characteristics, while still allowing the libraries to interact within a single application. Since Naiad supports sophisticated streaming algorithms that may include nested loops, it is a good testbed for general fault tolerance mechanisms. The ideas set out in this paper are applicable well beyond Naiad, and their implementation in a system without cyclic dataflow would be simpler. For example, we believe that some of the techniques we describe could be used, with modest effort, in the context of the Spark Streaming system [14].

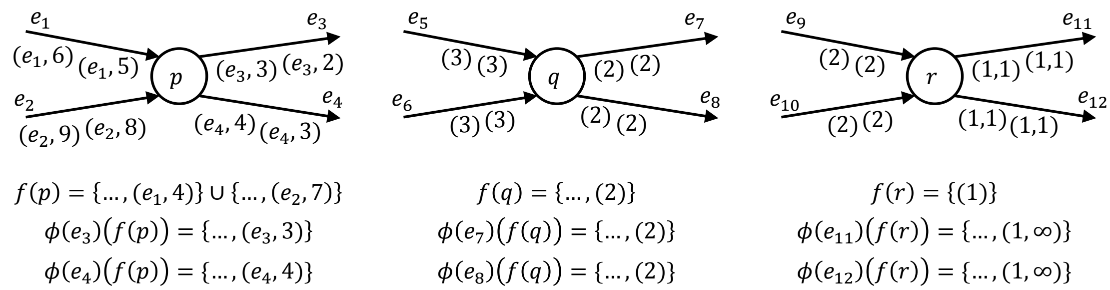
The next section sketches a number of popular fault tolerance policies and explains selective rollback. Section 3 sets out the Falkirk Wheel design, and Section 4 describes its implementation in the Naiad system. We finish with conclusions.

2 Tracking events for rollback

In this section we summarize a few rollback recovery schemes and comment on the design and performance tradeoffs they embody. In our discussion we refer to a processing node in a dataflow graph as a *processor*. A physical CPU in a distributed system may host multiple such processors. Later, we will fit several of the schemes into our common framework. In order to do this it is helpful to think of messages sent between processors as being tagged with partially-ordered logical times; often these tags are implicit. Many systems can inform a processor when it will not see any more messages with a particular logical time t. We call this a *notification* at time t. An *event* at time t means the delivery of either a message or a notification with that time. In the following we divide logical times into two broad categories: sequence numbers; and structured times, which include epochs.

2.1 Sequence numbers

Sequence numbers on ordered channels are illustrated in Figure 2(a). There is no need for notifications when using sequence numbers, since each message has a unique time. Rollback schemes that we model using sequence numbers are often used for systems where computation is not naturally structured using epochs. Such schemes



(a) Sequence numbers

(b) Epochs

(c) Structured times: epochs entering a loop

Figure 2: **Logical times for events.** Tuples $(\cdot)$ on input edges represent messages that have not yet been processed: the tuple shows the logical time of the message. Tuples on output edges represent sent messages. In Scheme (a), the logical time of a message with sequence number s on edge e is (e,s). p has processed the first 4 messages on edge e_1 and the first 7 on e_2, and has sent 3 messages on e_3 and 4 on e_4. Scheme (b) uses epoch numbers as logical times, so all messages in a given epoch have the same time. q has processed all the events in the first two epochs, and has sent all corresponding messages for those epochs. Scheme (c) uses structured logical times, generalizing epochs. r forwards incoming messages into a loop, which has a different time domain that includes an additional loop iteration counter. r has processed all events in the first epoch and sent all the messages it will ever produce with epoch 1 and any iteration count. The *frontier* $f(x)$ and *edge projection* $\phi(e)(f(x))$ at processor x are discussed in Section 3.

include the following:

Distributed Snapshots. Chandy and Lamport described a general algorithm for checkpointing an arbitrary distributed system [7]. Each process p receives messages from other processes in the system on a set of point-to-point channels $E(p)$. Periodically the system performs a global checkpoint: it chooses, for each process p and channel $e \in E(p)$, a sequence number s_e, and records the state C_p of p after all the messages up to s_e have been delivered on e and no others. The checkpoint also includes a sequence of undelivered messages M_e on each channel e. The design of the algorithm ensures that the chosen $\{C_p\}, \{M_e\}$ form a consistent global system state. Following a failure the system is restored to the state at the most recently saved checkpoint. This scheme is general, but has some practical drawbacks. Each process must be able to save a checkpoint at an arbitrary moment chosen by the system, which introduces overhead that is side-stepped by some designs below. Also in general all processes, even non-failed ones, must roll back to a prior checkpoint following a failure.

Exactly-once streaming. Streaming systems including Storm [5] and Millwheel [6] support stateful processors to which a message is guaranteed to be delivered exactly once, corresponding to the "eager checkpoint" regime of Figure 1. On receiving a message a processor persists its updated state and any resulting outgoing messages before acknowledging the processed message. As with the Chandy-Lamport algorithm, the persisted state encodes the effect of processing all messages up to the latest sequence number on each input, and no others. If a processor fails it is restored to its most-recently persisted state, which includes the effect of all acknowledged messages. This scheme has several benefits: it allows processors to choose locally when to checkpoint; it can guarantee high availability; non-failed processors need never be interrupted; and processors may join and leave the computation with low overhead since the system need not keep track of the dataflow topology. Drawbacks include a possible throughput penalty because all mutations to state must be persisted, and a possible latency penalty because sent messages must be acknowledged by their recipient process before the next incoming message can be acknowledged. The chain of dependent acknowledgements that builds up as a message's effects propagate may also limit the practical complexity of computations; for example iterative algorithms may be problematic.[1]

At-least once streaming. Both Storm and Millwheel also allow processors to be placed in a relaxed fault tolerance mode, in which the system does not eagerly check-

[1]Millwheel addresses some latency concerns by partitioning the state at each processor by a key function and performing work for distinct keys in parallel. It can also notify a processor when a low-watermark has passed, based on wall-clock timestamps. These notifications are not the same as the logical-time notifications in this paper, and we can model them as messages delivered on a virtual edge.

point each state update before proceeding to the next. This gives better performance, but must only be used for processors for which message deliveries are idempotent, or where it is tolerable to end up in a globally-inconsistent state. It is suitable for the "ephemeral" regime in our example.

2.2 Epochs

Some systems associate each input message with a particular batch or *epoch*, and structure computation (often using dataflow) so that all consequent messages and state updates can in turn be tagged with an epoch. These epochs can be used as coarse-grain logical times for events as illustrated in Figure 2(b).

A number of recent acyclic batch dataflow systems [8, 10, 13] share a fault tolerance model pioneered by the MapReduce system [8]. Each processor reads all of its inputs then implicitly receives a notification that the input is complete, writes its outputs, empties its state, and quiesces. We can think of all inputs and messages as being in a single epoch 0. Each system design specifies a subset of the edges in the dataflow and persists the messages sent on those edges. Following a failure the system chooses to restore each failed processor either to the state where it has processed no events, or where it has processed all events, based on a global function of which sent messages have been persisted.

This design has the appealing property that processors are always restored to an empty state after failure: this means that the (user-supplied) application logic in the processor need not include any checkpointing code. On the other hand, any work in progress at the time of a failure is lost and must be redone. Non-failed processors need only be interrupted if they have consumed messages from processors that were restored to the empty state. The model is well suited to off-line data-parallel workloads, where throughput in the absence of failures is paramount and delayed job completion is tolerable in the event of failures. A variation on the model, Spark Streaming [14], allows each processor to accept messages at an epoch $t+1$ after the messages at epoch t have been fully processed, matching the "batch" regime of our example. Unlike traditional streaming systems it does not let processors retain internal state between logical times.

2.3 Selective rollback

The Naiad system [12] achieves state of the art performance on the streaming iterative workload needed for the "lazy checkpointing" regime of our example, so we consider its fault-tolerance requirements. Naiad explictly assigns logical times to events. Each time is a tuple indicating an input epoch along with loop counters tracking progress through (possibly-nested) iteration as in Figure 2(c). A processor can request that a notification be delivered when a logical time is complete. Figure 3 shows a fragment of a simple Naiad dataflow graph made up of Select, Sum and Buffer processors. Below it is a timeline showing event deliveries and corresponding updates to the processor state, colored according to logical times. The Select processor translates a word into its numeric representation, and is stateless. The Sum processor accumulates a separate sum for each logical time. When notified that there will be no more messages at a given time, Sum outputs the accumulated sum for that time and then removes the sum from its local state. The Buffer processor records all messages it has seen.

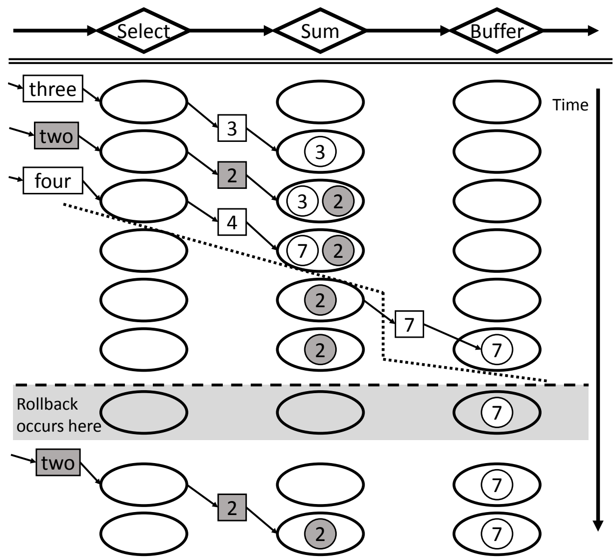


Figure 3: **Selective rollback.** Rectangles show messages and ovals processor state. A white background indicates a message or state corresponding to logical time A; a grey background to time B. The dashed line shows the point at which a processor will not receive any more messages at time A; a notification is delivered to the Sum processor after this point, causing it to send a message and discard its state related to A. Processors roll back to a state where they have consumed all messages at A and none at B.

All the Naiad computational libraries developed so far, including differential dataflow [11] which is the most complex, either keep no state at a processor or partition its state by logical time. Many Naiad processors, like the Sum in our example, delete the state corresponding to a time once that time is complete. It is thus desirable to allow a processor to wait until time t is complete before checkpointing the portion of local state that corresponds to t. Often this means no checkpoint need be saved, matching the software-engineering and performance characteristics of the systems in Section 2.2.

Naiad applications often include loops implemented as distributed sets of processors, and messages can flow around these loops with latencies of a millisecond or less. Restricting Naiad to suspend delivery of a message until all messages with earlier times had been processed would force a processor to stall waiting for the global coordinator to ensure that no "earlier" messages remained in the system, introducing a severe performance penalty. Consequently, Naiad processors may interleave the delivery of messages with different logical times.

We introduce the idea of selective rollback in order to support Naiad's twin performance requirements that processors must be able to interleave the logical times of delivered messages, and also checkpoint only state corresponding to completed times. In Figure 3 each processor makes a selective checkpoint after seeing the last time A message. Rather than saving its full current state, as is traditional, it saves the state it would contain having seen all time A messages and no time B messages. In general this checkpoint may not correspond to a state the processor has previously been in. The shaded rectangle shows a rollback during which each processor is set to its checkpointed state. Subsequently an upstream processor is re-executed, causing the time B message to be re-sent, and eventually the state of the system returns to that before the rollback. A scheme that did not support selective rollback would be forced to prevent the interleaved delivery of messages at different times, or to checkpoint non-empty state for the Sum processor, either of which would introduce a substantial performance penalty for Naiad.

3 The Falkirk Wheel framework

We now describe our general framework for rollback using logical times. As previously mentioned, after a failure the system chooses a set of logical times at each processor, which we call a *frontier*, and restores the processor to a state including the effect of the previously-delivered events with times in that frontier. We first discuss some restrictions on the use of logical times in our framework, and show that the existing schemes described in Sections 2.1 and 2.2 satisfy these restrictions. We then discuss a general algorithm for choosing frontiers that will result in rolling back to a globally consistent state.

3.1 From sets to frontiers

Not all sets of logical times can be used as frontiers: a frontier must be downward-closed. This means that if a time t is in the frontier, then so is every time $t' \leq t$. For a set T of times we write $\downarrow T = \{t' : t \in T \wedge t' \leq t\}$ for the operation that converts a set into the smallest frontier containing that set. The schemes described in Sections 2.1 and 2.2 already naturally adopt frontiers for rollback. For epochs logical times are totally ordered, so the restriction simply means that if we are rolling back to epoch t we must also include all previous epochs $t' < t$. For sequence numbers, recall that a logical time is a pair (e,s) where e is an edge and s is the sequence number of a message on that edge. We define a partial order on these times where $(e_1,s_1) \leq (e_2,s_2)$ if and only if $e_1 = e_2 \wedge s_1 \leq s_2$. This means that times are only comparable if they correspond to messages on the same edge, and within an edge sequence numbers indicate the natural ordering. For a processor with incoming edges $e_1 \dots e_n$ we associate the state in which the processor has consumed all messages up to s_i on edge e_i with the set

$$f^s_{e_1,\dots,e_n}(s_1,\dots,s_n) = \\ \{(e_1,1),\dots,(e_1,s_1)\} \cup \dots \cup \{(e_n,1),\dots,(e_n,s_n)\}.$$

This set is a frontier under the partial order above, and corresponds to the messages whose effects are included in a checkpoint at that state. Figure 2(a) shows the frontier $f(p) = f^s_{e_1,e_2}(4,7)$.

3.2 Bridging time domains

The *edge projection* functions $\phi(e)$ shown in Figure 2 allow us reason about rollback in a system containing processors with different logical time domains. For each edge e from processor p to q, $\phi(e)(f)$ maps a frontier f at p to a frontier in the time domain of q. The function $\phi(e)$ must be consistent with the behavior of p: it is a conservative estimate of the times that were "fixed" on e given the events in f at p. Specifically, p is guaranteed not to have produced any messages with times in $\phi(e)(f)$ as a result of processing an event with a time outside f. Informally, this means it is "safe" to roll q back to $\phi(e)(f)$ as long as p rolls back to a frontier at least as large as f. We could always set $\phi(e)(f) = \emptyset$, but instead would like to choose it as large as possible since larger ϕ will allow us to preserve more work during rollbacks.

In rollback schemes that use sequence numbers $\phi(e)(f)$ is defined naturally as illustrated in Figure 2(a). Suppose that when p is in state $f^s_{e_1,\dots,e_n}(s_1,\dots,s_n)$ it has sent s messages on outgoing edge e. Then

$$\phi(e)(f^s_{e_1,\dots,e_n}(s_1,\dots,s_n)) = \{(e,1),\dots,(e,s)\}.$$

(Conveniently, for our purposes we need not define $\phi(e)(f)$ for any frontier that does not correspond to a state in the history of p.) Systems that use epochs typically adopt the restriction that messages cannot be sent backwards in time. For these systems we can set $\phi(e)(f) = f$ everywhere, meaning an event at epoch t cannot result in a message at any epoch $t' < t$.

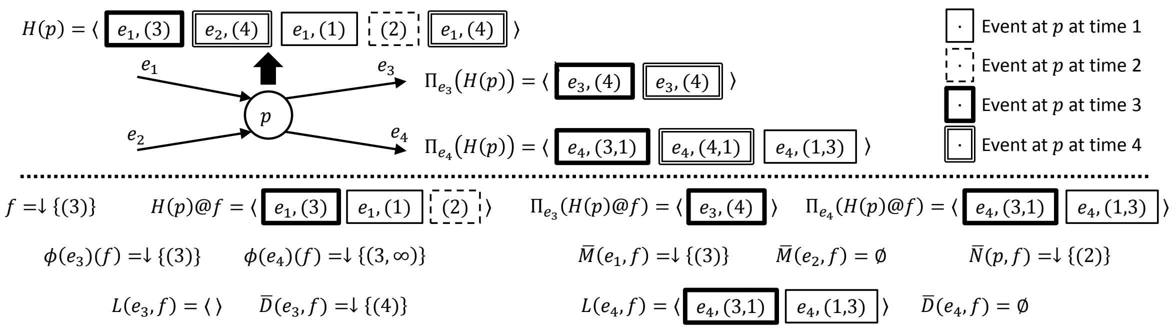


Figure 4: **Processor p filters its history on rollback.** $H(p)$ shows a sequence of events at p. Earlier events are to the left. There are three delivered messages, then a notification, then another message. $\Pi_e(H(p))$ shows the messages sent on edge e; so p sent two messages with time 4 on e_3. The border around an event or sent message shows the time of the event **at p**; so the first message on e_3 was sent at time 3, and the second at 4. The state of p after a rollback to the frontier $f = \{(1),(2),(3)\}$ is shown below the dotted line. The history and sent messages are filtered to retain only the events in f at p. $\bar{M}(e_1,f)$, $\bar{M}(e_2,f)$ and $\bar{N}(p,f)$ are the minimum frontiers containing the processed messages and notifications, respectively, in p's filtered history. The processor logged all sent messages on e_4 and none on e_3.

Figure 2(c) shows an example of a processor that receives messages tagged with epochs and forwards them in a new time domain: sent messages have times (t,c) where t is the epoch of the incoming message and c a loop counter. In this case we can choose $\phi(e)(f)$ to be $\{(t,c) : t \in f\}$, so ϕ "translates" between time domains.

Even in systems without loops, it may be useful to translate between time domains. A processor p may want to read from a computation structured using epochs and forward its input to a processor that takes eager checkpoints according to sequence numbers. In this case we might require p to forward all epoch 1 data before sending any epoch 2 data, if necessary buffering epoch 2 data until epoch 1 is complete. Suppose that in total p receives 73 messages in epoch 1, we could choose $\phi(e)(\{1\}) = \{1,\ldots,73\}$. A similar transformer could translate from sequence numbers to epochs, for example to construct epochs from sets of messages received at a processor within particular windows of wall-clock time.

3.3 Message re-ordering

We must impose a restriction on the semantics of processors that will be subject to selective rollback. This does not affect the schemes described in Sections 2.1 or 2.2, which never perform selective rollback. We require that such a processor p must be able to perform a limited re-ordering of messages on its input edges. Suppose e is an input edge to p, and contains a sequence of messages $\langle m_1,\ldots,m_k\rangle$ where m_1 is at the head of the sequence, i.e. m_1 was sent before m_2, and so on. Then p is at liberty to choose to remove and process from e any message m_i where $time(m_j) \not\leq time(m_i)\ \forall j < i$. So if m_5 is in epoch 1 and all of $m_1 \ldots m_4$ are in epochs 2 or greater, p can choose to process m_5 next. It does not have to be the case the p produces the same output under all re-orderings, but all of the outputs have to correspond to legal behaviors of the computation. This restriction is intuitively necessary if we want to legally be able to roll p back to a state in which it has processed all the epoch 1 events and none from later epochs, independent of the order that the messages appeared on e. It is satisfied by all Naiad processors we are aware of.

3.4 Checkpoints and processor history

When deciding what frontiers a processor can be rolled back to we need to take into account exactly what information p has persisted. For example, processors can in general only roll back to a fixed set of frontiers for which they took checkpoints. Also, some processors log sent messages and others do not.

We start with notation. $H(p)$ is the *history* at p at the time of the rollback, i.e. the sequence of events that it has processed, and $H(p)@f$ is the subsequence of $H(p)$ keeping only events with times in a frontier f. (For processors that don't perform selective rollback, $H(p)@f$ is always a prefix of $H(p)$.) For $e \in Out_e(p)$, the output edges at p, $\Pi_e(H(p))$ is the sequence of messages that p sent on e as a result of processing the events in $H(p)$, and $\Pi_e(H(p)@f)$ is the sequence of messages that p would have sent on e if it had processed only the events in $H(p)@f$. When $H(p)@f$ is not a prefix of $H(p)$, $\Pi_e(H(p)@f)$ may not be a subsequence of $\Pi_e(H(p))$, though it is for all the processors we have studied. Figure 4 shows an example history.

In general we don't have access to $H(p)$, $\Pi_e(H(p))$, $H(p)@f$, or $\Pi_e(H(p)@f)$. Instead, we assume that there is some sequence of frontiers $F^*(p) = \{f_1,\ldots,f_n\}$, where $f_i \subset f_{i+1}$, that are available for p to roll back to

$F^*(p)$	Set of available frontiers
For each $f \in F^*(p)$	
$S(p,f)$	Internal state at f
$\bar{N}(p,f)$	Processed notification frontier at f
For each $f \in F^*(p)$, $d \in In_e(p)$	
$\bar{M}(d,f)$	Processed message frontier from d at f
For each $f \in F^*(p)$, $e \in Out_e(p)$	
$\phi(e)(f)$	Edge projection on e at f
$L(e,f)$	Messages logged on e at f
$\bar{D}(e,f)$	Discarded message frontier on e at f

Table 1: **State that must be available to processor p on rollback.** Most processors can approximate some values and do not need to explicitly persist all of them.

because it has persisted appropriate information about them, summarized in Table 1. For a processor that has not failed, $F^*(p)$ may contain the special frontier $\top$ that includes all event times.

For each $f \in F^*(p)$ we assume p has persisted enough information to recover $\phi(e)(f)$ for each $e \in Out_e(p)$ and to be able to restore its internal state to $S(p)(f)$, which reflects the effects of all events in $H(p)@f$. Depending on p's policy it may have logged some, all, or none of its sent messages. We write $L(e,f)$ for the subsequence of $\Pi_e(H(p)@f)$ that have been logged and $D(e,f) = \Pi_e(H(p)@f) \setminus L(e,f)$ for those that were discarded. Let $M(d,f)$ be the sequence of messages on $d \in In_e(p)$, the input edges to p, that were processed by p in $H(p)@f$, and $N(p,f)$ the sequence of notifications processed by p in $H(p)@f$. For each $f \in F^*(p)$ we assume that p has stored a conservative estimate of $\bar{M}(d,f)$, $\bar{N}(p,f)$, and $\bar{D}(e,f)$, respectively the smallest frontier containing its delivered messages, notifications, and discarded messages:

$$\begin{aligned}\bar{M}(d,f) &= \downarrow\{t : (d,m) \in M(d,f) \wedge t = time(m)\}\\ \bar{N}(p,f) &= \downarrow\{t : t \in N(p,f)\}\\ \bar{D}(e,f) &= \downarrow\{t : m \in D(e,f) \wedge t = time(m)\}.\end{aligned}$$

Note that $time(m)$ for $m \in D(e,f)$, and thus also $\bar{D}(p,f)$, is in the domain of the process that will *receive* the message, not p's time domain.

In many cases, p need not explicitly store all the state in Table 1. For most schemes that use structured times, including epochs, $\phi(e)(f)$ is independent of p's history. It is always safe to overestimate $\bar{M}(d,f) = \bar{N}(p,f) = f$. If the processor logs all messages, $\bar{D}(e,f) = \emptyset$. For most processors that discard all messages it is safe to use the approximation $\bar{D}(e,f) = \phi(e)(f)$, though processors that send "into the future," like some differential dataflow processors [11], must explicitly keep track of which times they have discarded messages for. Finally, in the common case (as in Section 2.2) that p is an epoch-based processor that keeps no state between epochs, sends all messages with the epoch of the event that caused the message, and doesn't log any messages, it need not persist anything. Such processors can adopt

$$S(p,f) = \emptyset \qquad L(e,f) = \langle\rangle$$
$$\phi(e)(f) = \bar{M}(d,f) = \bar{N}(p,f) = \bar{D}(e,f) = f$$

and need not even save $F^*(p)$ since they can restore to any requested frontier.

3.5 Consistent frontiers for rollback

In the event of one or more failures, the system must choose a frontier $f(p)$ at each processor p such that the system as a whole rolls back to a consistent global state. We list a set of constraints that, if satisfied, ensure a consistent rollback. We have published a theoretical paper that proves the correctness of the constraints. We show via a refinement mapping that a system which obeys the Falkirk Wheel rollback constraints on failure implements (has external effects indistinguishable from) a higher-level system without failures.

The first constraint says that a processor p may not restore to a frontier f if there is any message m awaiting delivery on an edge $e \in In_e(p)$ with $time(m) \in f$. This restriction can be satisfied by saving a checkpoint for frontier f only after all the times in f are complete at p. This behavior is already adopted by the systems described in Sections 2.1 and 2.2 and is easy to enforce for systems such as Naiad that support notification.

The next constraint deals with discarded messages:

$$\forall e \in Out_e(p),\;\; \bar{D}(e, f(p)) \subseteq f(dst(e))$$

where $dst(e)$ is the processor that p sends to on e. Informally, this says that a processor downstream of p cannot roll back so far that it would need to re-receive any messages that p has discarded.

The third constraint deals with delivered messages:

$$\forall d \in In_e(p),\;\; \bar{M}(d,f) \subseteq \phi(d)(f(src(d)))$$

where $src(d)$ is the processor that sends to p on d. This says that a processor must roll back far enough that any delivered messages are within the frontier "fixed" by the upstream processor's rollback, in the sense described in Section 3.2.

The final constraints deal with notifications and are motivated by the example in Figure 5, in which $\phi(e)(f) = f$ for all e. Processors p and q have each received a notification for time 1, in response to which p sent a message at time 1 on e_1 and q did nothing. The message arrived at r, which sent nothing in response, at

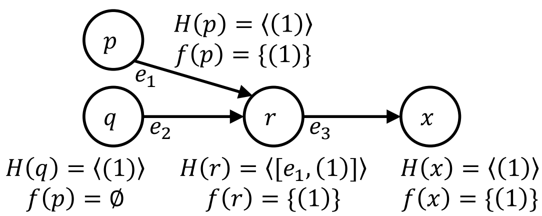


Figure 5: **Without notification frontiers rollback can lead to inconsistent state.** See Section 3.5 for details.

which point x received a notification for time 1 indicating that it will not receive any more time 1 messages. According to the preceding constraints the system could roll back to the frontiers shown in the Figure; in particular $f(p)$ can be set to $\emptyset$ since $\bar{M}(e_2, \{(1)\}) = \emptyset$. Suppose, after rollback, q behaves differently on receiving the notification and sends a message at time 1 on e_2, which r forwards on e_3. Then x will receive a new message at time 1 even though it has rolled back to a history in which it received a notification promising this will never happen. The problem cannot be fixed by simply adding a new pairwise constraint between r and x: in the example they already roll back to the same frontier. Instead we introduce an auxiliary variable at each p, the *notification frontier* $f_n(p)$, and add additional constraints:

$$f_n(p) \subseteq f(p)$$
$$\bar{N}(p, f) \subseteq f_n(p)$$
$$\forall d \in In_e(p),\;\; f_n(p) \subseteq \phi(d)(f_n(src(d))).$$

The notification frontiers are not used in the rollback; they simply act to constrain $f(p)$ to ensure consistency. Notification frontiers can be "omitted" by setting $\bar{N}(p, f) = f_n(p) = \emptyset$ everywhere in systems without notifications.

3.6 Choosing consistent frontiers

Figure 6 shows an algorithm to find a frontier at each processor that will satisfy the constraints. As long as $\emptyset \in F^*(p)\ \forall\ p$, meaning every processor can roll back to its initial state, it is always possible to choose values for f' and f'_n while executing the fixed point. In this case the algorithm will always converge since neither f nor f_n ever increases, and $f(p) = f_n(p) = \emptyset\ \ \forall\ p$ satisfies all constraints.

The choice of $f'_n(p)$ indicates a maximum over a subset of all frontiers. If frontiers are not totally ordered, any maximal element can be chosen. In all practical systems we have considered either frontiers are totally ordered, notifications are not supported, or $\bar{N}(p, f) = f(p)$ everywhere (so $f_n(p) = f(p)$). In such systems the algorithm will at every p return the maximal globally-consistent frontier (and the term $\bar{N}(p, f'(p)) \subseteq g_n$ is unnecessary

Initially: $\forall p,\;\; f(p) = f_n(p) = \max\{f \in F^*(p)\}.$

Continue until fixed point:

$$\begin{aligned} f'(p) = \max\{ & g \in F^*(p) \text{ such that } g \subseteq f(p) \\ & \wedge \forall e \in Out_e(p),\;\; \bar{D}(e, g) \subseteq f(dst(e)) \\ & \wedge \forall d \in In_e(p),\;\; \bar{M}(d, g) \subseteq \phi(d)(f(src(d))) \\ & \qquad \wedge \bar{N}(p, g) \subseteq \phi(d)(f_n(src(d)))\} \end{aligned}$$

$$\begin{aligned} f'_n(p) = \max\{ & g_n \text{ such that } g_n \subseteq f'(p) \cap f_n(p) \\ & \wedge \bar{N}(p, f'(p)) \subseteq g_n \\ & \wedge \forall d \in In_e(p),\;\; g_n \subseteq \phi(d)(f_n(src(d)))\} \end{aligned}$$

Figure 6: **Algorithm to choose consistent frontiers for rollback.**

since it will always be satisfied). For these systems, adding choices of f to $F^*(p)$ at any p will never cause $f(p')$ to get smaller for any p'—a valid set of frontiers remains valid as more checkpoints are saved.

After frontier $f(p)$ is chosen for rollback at p, its state is reset as follows:

$$F^{*\prime}(p) = \{f' : f' \in F^*(p) \wedge f' \subseteq f(p)\}$$
$$H'(p) = H(p) @ f(p)$$
$$S'(p) = S(p, f(p))$$
$$Q'(e) = L(p, f(p)) \not@ f(dst(e))\;\; \forall e \in Out_e(p)$$

where $Q'(e)$ is a sequence of messages to send on e and $L(p, f(p)) \not@ f(dst(e))$ is the messages in $L(p, f(p))$ whose times are not contained in $f(dst(e))$. Figure 7 shows some examples of dataflow graphs with different characteristics, and the frontiers that are chosen for rollback.

4 Fault tolerance in Naiad

In order to evaluate its performance and ease of use, we have added prototype support for Falkirk Wheel fault tolerance to Naiad [12]. Naiad is structured as a low-level system layer, a set of commonly-used framework libraries, and a few application-specific processors. The Lindi framework is a library of processors that keep no state between logical times, with similar functionality to Spark [13] plus native support for iteration. Differential Dataflow [11] is a general-purpose library for incremental iterative computation, in which processors generally keep state to allow them to respond quickly to updates. As we explain in the following, we have added appropriate checkpointing and logging to all the Lindi and Differential Dataflow processors, as well as hooks to make it easy to add fault tolerance to custom processors.

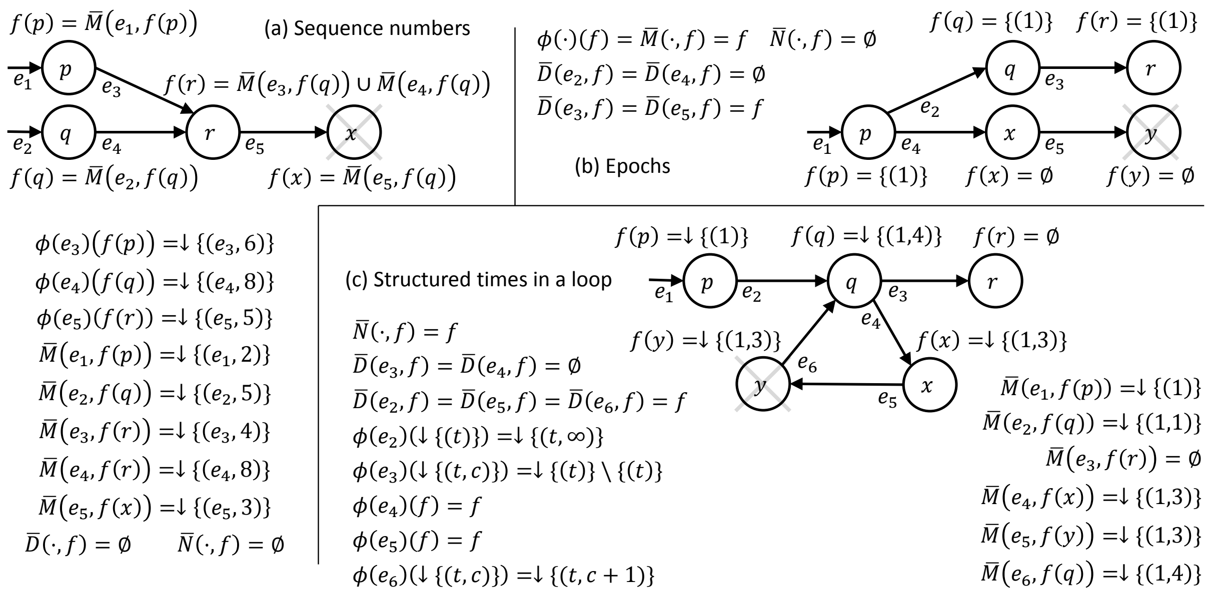


Figure 7: **Some examples of rollback.** Panel (a) shows a system based on sequence numbers. Processor x has failed. All processors log all outputs ($\bar{D}(\cdot, f) = \emptyset$) and there are no notifications. All processors roll back to a state where they have sent at least as many messages as their upstream processors have consumed. Panel (b) shows a system based on epochs, similar to Spark [13], where y has failed. Processor p acts like a Spark Resilient Distributed Dataset (RDD) and has logged all its outputs; no other processors have saved any state. Both x and y must roll back to their initial state, while p, q and r do not need to roll back. Panel (c) shows a system like Naiad with a loop, where y has failed. Processor q logs its sent messages, but no other processors do. Processor p sends messages into the loop along e_2 and q sends them out of the loop along e_3. Processor q increments the loop counter coordinate of the time of each message it receives on e_5, and then forwards it on e_6. As a result, q can roll back to $\downarrow\{(1,4)\}$ even though y rolls back to $\downarrow\{(1,3)\}$. Thus q re-sends its logged messages at time $(1,4)$ on e_4, "restarting" the processing in the loop.

4.1 Logging and checkpointing support

For simplicity, for checkpointing purposes we impose the lexicographic (total) ordering on all Naiad logical times at a given processor. Since logical times at a processor are totally ordered a frontier can be summarized by a single largest element, and frontiers are also totally ordered.

Naiad already requires that messages are serializable in order to support distributed operation. Any processor, with no additional programming effort, can request that the system log all of its delivered messages and notifications; i.e., its full history $H(p)$ in the notation of Section 3. This gives any deterministic processor without external side-effects full fault tolerance with no software-engineering effort: it can be automatically rolled back to any frontier by replaying the filtered history and forwarding any resulting messages that are needed by downstream processors after their rollback. This is a good fallback option, but the history grows without bound so it is not suitable for long-running streaming applications.

The system can automatically keep track of $\bar{N}$, $\bar{M}$ and $\bar{D}$ for any processor. A processor can elect to log some or all sent messages, again with no additional programming effort. A processor can also declare that it keeps no state between logical times, and we call such a processor "stateless" even though it may accumulate state within a time. Alternatively it can elect to receive checkpoint callbacks. If such a processor requests a notification for time t then it may selectively checkpoint its state up to t after the notification has been processed. Stateful processors are also periodically (lazily) informed when new times become complete, and can choose to selectively checkpoint based on local policy.

We identify all Lindi processors as stateless, and by default suppress logging of sent messages meaning that the processors incur no fault tolerance overhead. A particular instance of a processor may be told by an application developer to log its sent messages, in which case it behaves like a Spark RDD and acts like a "firewall" preventing upstream processors from rolling back in the event of a downstream failure.

We have added selective incremental checkpointing to all Differential Dataflow processors that keep state. Since the state is internally stored differentiated by logical time, this was straightforward.

4.2 Garbage collection

A fault tolerance design that targets practical streaming systems must address the issue of garbage-collecting persisted state, since it will otherwise grow indefinitely. Let

$$\Xi(p,f) = \{f, \bar{N}(p,f),\\ \{\bar{M}(d,f) : d \in In_e(p)\}, \{\bar{D}(e,f) : e \in Out_e(p)\}\}$$

be the metadata about the checkpoint needed for the rollback algorithm.

Each time a processor p receives an acknowledgement from storage that $\Xi(p,f)$, $S(p,f)$ and $L(p,f)$ have all been persisted for some f, it sends $\Xi(p,f)$ to a monitoring service. This service keeps track of $F^*(p)$ for all processors in the system. It starts with $F^*(p) = \emptyset$ and updates it every time it receives new metadata. The monitor runs an incremental implementation of the fixed point algorithm of Figure 6 in a local Naiad runtime independent of the main application. When an update arrives the algorithm determines the new maximum rollback frontier at every processor given the persisted checkpoints. We assume that storage is reliable, so this rollback frontier is a low-watermark: the processor will never need to roll back beyond it in any failure scenario. Every time the low-watermark frontier at p increases to f the monitoring service informs p, which is at liberty to garbage-collect $\Xi(p,f')$ and $S(p,f)$ for any $f' \subset f$. Processors q that send to p are also notified, and can discard any messages in $L(e,\cdot)$ with times in f for $e \in In_e(p)$. Since the monitoring service is deterministic, monotonic, and used only for garbage collection, it could easily be replicated though our prototype does not do this.

4.3 Inputs and outputs

The fault-tolerance properties of a streaming system can only be considered in the context of its streaming inputs and outputs. We assume that the services producing and consuming streams support fault tolerance via acknowledgement and retry. For an input, this means that the service will keep a batch of data available, and re-send if requested, until the batch has been acknowledged. For an output this means that we must be willing to re-send a batch of data multiple times until it is acknowledged by the recipient. These assumptions are compatible with services such as Kafka [3] and Azure Event Hubs [1].

Input and output acknowledgements can be handled by our existing garbage-collection mechanism. Processors that read external inputs are marked as stateless. Once such a processor is informed by the monitor that it will never need to roll back beyond a frontier f it can acknowledge all inputs ingested at times in f. A processor that sends external outputs is marked stateful but saves no checkpoints; instead it tells that monitor that f has been persisted once the external service has acknowledged all records sent at times in f, at which point the rest of the system may discard state that would be needed to regenerate those output records. We can use this mechanism to construct a stateless pipeline in which input records are only acknowledged once outputs have been consumed; or by adding persistent state in the pipeline we can decouple input receipt from output acknowledgement.

4.4 Recovery from failure

A processor p typically discovers the failure of another processor q by the failure of a network connection to a remote computer. When this happens p continues to work, buffering output to q in case the connection is reestablished. When q's failure is confirmed by a failure detector, the system pauses all processors and uses the monitoring service to determine appropriate rollback frontiers. All non-failed processors p have $\top$ temporarily added to $F^*(p)$, and the incremental algorithm computes the maximal frontiers needed for rollback given the failed processors. A non-failed processor with a frontier earlier than $\top$ can typically roll back by discarding in-memory state rather than restoring from stable storage. Any needed logged messages $Q'(e)$ are placed in appropriate output queues, and the processors are restarted. With some additional work Naiad could be modified to allow pipelines of non-failed processors to continue without pausing.

5 Conclusions

We present a new framework for rollback recovery, suitable for high throughput streaming systems. We show a general mechanism to determine a globally consistent state given a collection of local checkpoints and logs organized in terms of logical times, and information about the local behavior of processors that constrains what logical times may be assigned to messages sent in response to events. The generality of the mechanism makes it possible for processors to use flexible local policies to decide when to take checkpoints, and as a result get substantial performance and software engineering benefits.

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