# A Cloud Native Platform for Stateful Streaming

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## Abstract

We present the architecture of a cloud native version of IBM Streams, with Kubernetes as our target platform. Streams is a general purpose streaming system with its own platform for managing applications and the compute clusters that execute those applications. Cloud native Streams replaces that platform with Kubernetes. By using Kubernetes as its platform, Streams is able to offload job management, life cycle tracking, address translation, fault tolerance and scheduling. This offloading is possible because we define custom resources that natively integrate into Kubernetes, allowing Streams to use Kubernetes' eventing system as its own. We use four design patterns to implement our system: controllers, conductors, coordinators and causal chains. Composing controllers, conductors and coordinators allows us to build deterministic state machines out of an asynchronous distributed system. The resulting implementation eliminates 75% of the original platform code. Our experimental results show that the performance of Kubernetes is an adequate replacement in most cases, but it has problems with oversubscription, networking latency, garbage collection and pod recovery.

## **1** Introduction

Stream processing enables fast analysis of a high volume of newly arriving data. While industry and academia have produced many stream processing systems in the past two decades [1–10], they all share three defining characteristics:

- A programming model that naturally exposes data, task and pipeline parallelism. Multiple levels of parallelism allow streaming applications to scale with the number of data sources and available hardware.
- Interesting streaming applications tend to be stateful. General purpose stream processing can perform nontrivial computations, directly providing answers to users. Such computations typically require maintaining state.
- A platform and runtime system capable of exploiting the available parallelism while preserving application state. The kind of platform streaming systems require approaches

sponsible for distributing generic user code across a cluster of compute nodes, arbitrating connections between parts of the applications on different nodes and managing the life cycle of the application as well as all component pieces. In the service of managing the applications on the cluster, streaming platforms must also manage the cluster itself: track nodes leaving and entering, allocate resources and schedule applications.

Recently a new kind of technology has emerged for generic cluster management: cloud platforms built on containers. They are a sweet-spot between clouds that expose virtual machines and fully hosted single services. Container based cloud environments are fully generic, but still remove the need for users to manage an underlying system. Users build container images with programs, libraries and files in the exact configuration they need. Users specify how to deploy and manage the containers that comprise their application through configuration files understood by the cloud platform.

Because the user is not responsible for managing the cluster of systems in a container based cloud platform, the cloud platform is. Unlike platforms for streaming systems, cloud platforms do not *approach* general purpose cluster management, but *are* general purpose cluster management. One of the most popular such cloud platforms is Kubernetes [11], which grew out of Google's experience managing containers for their infrastructure and applications [12].

Because general purpose cluster management is so valuable, Kubernetes has been widely adopted by industry to manage their own internal workloads. The convergence of public cloud platforms with on-premise cluster management is called *hybrid cloud*. Due to the shared underlying cloud platform, workloads can migrate between public and private settings.

The ubiquity of cloud platforms like Kubernetes also means there is no escaping them: they will be used to manage all kinds of software in all settings. For simple workloads, migrating to cloud platforms simply requires building the existing software into containers and deploying as needed. Scaling and fault tolerance are also trivial for simple workloads: just start more containers. But this approach is not appropriate for workloads such as stream processing that already have their

general purpose cluster management. Such a platform is re-\*Both authors contributed equally to this work.

own management platform and stateful applications. Taking the simple approach will create a platform-within-a-platform which is difficult to manage, understand and maintain.

Instead, systems such as streaming platforms need to be rearchitected for cloud platforms such as Kubernetes. The new architectures need to be designed around the fact that cloud platforms already provide the basics of cluster management.

This paper presents the design of a cloud native version of IBM Streams, targeting Kubernetes as the cloud platform. Cloud native Streams relies on Kubernetes for job management, life cycle tracking, scheduling, address translation and fault tolerance. The resulting implementation reduces the platform code base by 75%. We achieved this reduction in code size by starting from the question of what existing Streams applications need to execute, rather than trying to reimplement the existing Streams platform in Kubernetes. We believe our experience with this rearchitecture will apply to any system which also required its own management platform. This paper makes the follow contributions:

- The cloud native patterns used to build cloud native Streams (§ 4). Composing these patterns—controllers, conductors, coordinators and causal chains—enable us to construct a deterministic platform out of an asynchronous distributed system. These patterns are available as an open source library at http://www.github.com/ ibm/cloud-native-patterns.
- 2. The architecture of cloud native Streams (§ 5), deepdives on specific features (§ 6), and lessons learned (§ 7).
- Experimental results comparing the performance of cloud native Streams to a legacy version of Streams (§ 8). Network latency, tolerance to oversubscription, garbage collection and pod recovery are worse in the cloud native version. We present these results to help improve Kubernetes.

## 2 Related work

Cloud native applications are defined by their leverage of cloud orchestrators such as Kubernetes [11] or Apache Mesos [13] and their microservice architecture. Derived from the "Twelve-Factor App" guidebook [14], the microservice architecture is an evolution of the traditional monolithic and service-oriented architectures, common to enterprise applications. It favors small, stateless, siloed components with clean interfaces to maximize horizontal scalability and concurrent development while minimizing downtimes. The most commonly published works about cloud-native transformation of legacy workloads cover stateless applications [15–23].

Facebook developed Turbine, which is a cloud native platform for managing their streaming applications on their Tupperware container platform [24]. The main features are a scalable task scheduler, auto-scaler and consistent and reliable update mechanism. Turbine running on Tupperware is similar to cloud native Streams running on Kubernetes, with the exception that Kubernetes handles much more of the platform responsibilities. In the area of relational databases, Amazon [25] and Alibaba [26] undertook the redesign of existing databases to better fit their respective cloud infrastructure.

For stateful applications, the *lift-and-shift* [27] approach is more common than a complete redesign of the supporting platform, often accompanied with a shim operator that exposes some of the application's concepts to the cloud platform through the application's native client interface [28–30].

# **3** Background and Motivation

## 3.1 IBM Streams

IBM Streams is a general-purpose, distributed stream processing system. It allows users to develop, deploy and manage long-running streaming applications which require highthroughput and low-latency online processing.

The IBM Streams platform grew out of the research work on the Stream Processing Core [31]. While the platform has changed significantly since then, that work established the general architecture that Streams still follows today: job, resource and graph topology management in centralized services; processing elements (PEs) which contain user code, distributed across all hosts, communicating over typed input and output ports; brokers publish-subscribe communication between jobs; and host controllers on each host which launch PEs on behalf of the platform.

The modern Streams platform approaches general-purpose cluster management, as shown in Figure 5. The responsibilities of the platform services include all job and PE life cycle management; domain name resolution between the PEs; all metrics collection and reporting; host and resource management; authentication and authorization; and all log collection. The platform relies on ZooKeeper [32] for consistent, durable metadata storage which it uses for fault tolerance.

Developers write Streams applications in SPL [33] which is a programming language that presents streams, operators and tuples as abstractions. Operators continuously consume and produce tuples over streams. SPL allows programmers to write custom logic in their operators, and to invoke operators from existing toolkits. Compiled SPL applications become archives that contain: shared libraries for the operators; graph topology metadata which tells both the platform and the SPL runtime how to connect those operators; and external dependencies. At runtime, PEs contain one or more operators. Operators inside of the same PE communicate through function calls or queues. Operators that run in different PEs communicate over TCP connections that the PEs establish at startup. PEs learn what operators they contain, and how to connect to operators in other PEs, at startup from the graph topology metadata provided by the platform.

We use "legacy Streams" to refer to the IBM Streams version 4 family. The version 5 family is for Kubernetes, but is not cloud native. It uses the lift-and-shift approach and creates a platform-within-a-platform: it deploys a containerized version of the legacy Streams platform within Kubernetes.

#### 3.2 Kubernetes

Borg [34] is a cluster management platform used internally at Google to schedule, maintain and monitor the applications their internal infrastructure and external applications depend on. Kubernetes [11] is the open-source successor to Borg that is an industry standard cloud orchestration platform.

From a user's perspective, Kubernetes abstracts running a distributed application on a cluster of machines. Users package their applications into containers and deploy those containers to Kubernetes, which runs those containers in *pods*. Kubernetes handles all life cycle management of pods, including scheduling, restarting and migration in case of failures.

Internally, Kubernetes tracks all entities as *objects* [35]. All objects have a name and a specification that describes its desired state. Kubernetes stores objects in etcd [36], making them persistent, highly-available and reliably accessible across the cluster. Objects are exposed to users through *resources*. All resources can have *controllers* [37], which react to changes in resources. For example, when a user changes the number of replicas in a ReplicaSet, it is the ReplicaSet controller which makes sure the desired number of pods are running. Users can extend Kubernetes through *custom resource definitions* (CRDs) [38]. CRDs can contain arbitrary content, and controllers for a CRD can take any kind of action.

Architecturally, a Kubernetes cluster consists of nodes. Each node runs a *kubelet* which receives pod creation requests and makes sure that the requisite containers are running on that node. Nodes also run a *kube-proxy* which maintains the network rules for that node on behalf of the pods. The *kube-api-server* is the central point of contact: it receives API requests, stores objects in etcd, asks the scheduler to schedule pods, and talks to the kubelets and kube-proxies on each node. Finally, *namespaces* logically partition the cluster. Objects which should not know about each other live in separate namespaces, which allows them to share the same physical infrastructure without interference.

#### 3.3 Motivation

Systems like Kubernetes are commonly called "container orchestration" platforms. We find that characterization reductive to the point of being misleading; no one would describe operating systems as "binary executable orchestration." We adopt the idea from Verma et al. [34] that systems like Kubernetes are "the kernel of a distributed system." Through CRDs and their controllers, Kubernetes provides state-as-a-service in a distributed system. Architectures like the one we propose are the result of taking that view seriously.

The Streams legacy platform has obvious parallels to the Kubernetes architecture, and that is not a coincidence: they solve similar problems. Both are designed to abstract running arbitrary user-code across a distributed system. We suspect that Streams is not unique, and that there are many non-trivial platforms which have to provide similar levels of cluster management. The benefits to being cloud native and offloading the platform to an existing cloud management system are:

- Significantly less platform code.
- Better scheduling and resource management, as all services on the cluster are scheduled by one platform.
- Easier service integration.
- Standardized management, logging and metrics.

The rest of this paper presents the design of replacing the legacy Streams platform with Kubernetes itself.

# 4 Cloud Native Patterns

We present the key abstractions that made the migration of IBM Streams from a legacy platform to a cloud native platform possible: controllers, conductors, coordinators and causal chains. The patterns are available as an open source Java library at http://www.github.com/ibm/cloud-native-patterns.

## 4.1 Controllers

Kubernetes defines controllers as "control loops that tracks at least one resource type" [37]. We constrain that definition further: in cloud native Streams, a controller is a control loop that tracks a single resource type. Controllers take some action on creation, modification and deletion of a resource type. As with regular resources, custom resources can be monitored using controllers. Cloud native Streams makes extensive use of custom resources to store platform related state (Figure 4). For each custom resource, it implements a concurrent controller deployed within the instance operator. The instance operator also uses controllers for traditional Kubernetes resources such as pods, nodes, and namespaces.

In cloud native Streams, a resource controller is responsible for monitoring events on a single resource, saving state updates for this resource in a local cache, and executing any action as a result of these events. We use the microBean Kubernetes Controller library [39] as a starting point for our controller abstraction. It implements both the informer and reflector patterns as defined in the Go client [40]. In its most essential form, a cloud native Streams controller is built by defining a set of three event callbacks (onAddition, onModification, onDeletion), a resource store, and providing both callbacks and store to an internal microBean controller instance.

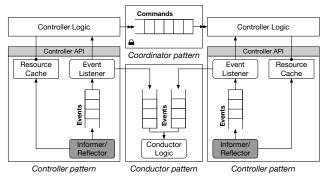


Figure 1: Clound native patterns: controller, conductor and coordinator. This example shows two controllers and one conductor. The controller on the left uses the coordinator pattern to update resources owned by the controller on the right. A conductor monitors events from both resources.

The *controller pattern* in Figure 1 depicts the relationships between these components. An *event listener* categorizes notifications it receives from the microBean informer into addition, modification and deletion events on resources. Cloud native Streams controllers, which derives from an event listener, implement the actions to take in response to these events. The resource cache is used by the microBean reflector to maintain a cached view of the resource pool based on the streams of event it has received.

## 4.2 Conductors

In contrast to controllers, the *conductor pattern* (bottommiddle of Figure 1) observes events from multiple resources and does not save state updates in a local cache. Instead, they are concurrent control loops that maintain a state machine that transitions based on resource events, all towards a final goal. Conductors do not own any resources. Rather, they register themselves with existing controllers as generic event listeners which receive the same notifications that each controller does.

The conductor pattern solves the problem of synchronizing a particular action based on asynchronous events generated by multiple actors. In cloud native Streams, we encountered the conductor pattern in two main cases: job submission and pod creation for PEs. For jobs, we need to know when to move the job's status from the initial Submitting to the final Submitted state. A job is not fully submitted until all of the resources that comprise it have been fully created. Before we can create a pod for a PE, we must first ensure that all of its dependencies exist, such as secrets or its ConfigMap.

In both cases, it is necessary to listen to multiple resource events and maintain local tracking of the status of those resources in order to arrive at the goal.

#### 4.3 Coordinators

When asynchronous agents need to modify the same resource, we use the *coordinator pattern* (top-middle of Figure 1). The coordinator pattern implements a multiple-reader, singlewriter access model by granting ownership of the resource to a single agent and serializing asynchronous modification requests coming from other agents. Coordinators are synchronous command queues that serially execute modification commands on resources. In cloud native Streams, this pattern means that the controller for a resource owns that resource, and other controllers which want to modify it must make requests to that controller.

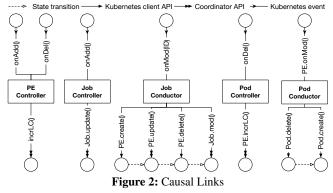
Many situations in cloud native Streams involve concurrent agents wanting to modify resource they interact with. For example, a PE's launch count tracks how often the platform has started a PE. There are two instances when we must increment the PE launch count: pod failure and PE deletion. However, different agents handle those two events. Allowing them to asycnhronsouly modify the PE's launch would lead to race conditions.

Instead, we use the coordinator pattern. When a pod fails, it must be restarted. Our pod controller overrides the default

behavior of letting the kubelet restart the pod. When the pod controller is notified of a failed pod, it must increase the restart count of its owning PE. Doing so directly through a Kubernetes update command could lead to race conditions between the PE controller and the pod controller. Instead, we use the PE coordinator interface to let the PE controller execute that command for us.

## 4.4 Causal Chains

A *causal link* (Figure 2) is a single actor responding to a single resource change by synchronously changing one or more other resources. These logical state transitions are atomic and composable. A *causal chain* (Figure 3) is the composition of multiple causal links where the result of one is the input to another. It is an asynchronous sequence of deterministic actions that implements a logical state transition across multiple resources. Unlike the other patterns, causal links and chain are not themselves actors in the system. They are a pattern of behavior that emerges from the interaction of multiple actors.



Causal chains are an abstraction that derives from two principles: operational states have a single source of truth provided by Kubernetes, and these states can only be synchronously modified in a single place in the system. As a consequence, causal chains necessarily span across multiple actors: modifications initiated by one actor on a resource it controls cause another actor to make modifications to its own resource.

$$\longrightarrow \text{onAdd} \longrightarrow \overset{\text{PE}}{\text{controller}} \xrightarrow{\text{incrLC}()} \xrightarrow{\text{w}} \xrightarrow{\text{PE.onMod}()} \xrightarrow{\text{Pod}} \xrightarrow{\text{Pod.create}()} \xrightarrow{\text{order}} \xrightarrow{\text{Pod.create}()} \xrightarrow{\text{Figure 3: Causal Chain}}$$

In cloud native Streams, a causal link drives the creation of a pod for a PE. The pod conductor is the only actor which can create pods for PEs, and it only reacts to changes to a PE's launch count. It composes with four other causal links to create causal chains:

- 1. *PE creation*. The PE controller reacts to a new PE by incrementing the launch count through the PE coordinator.
- 2. *Voluntarily PE deletion*. The PE controller recreates the PE resource, which eventually leads to (1).
- 3. *Pod failure or deletion*. The pod controller increments the PE launch count through the PE coordinator.
- 4. Job submission. The job conductor checks if any PEs

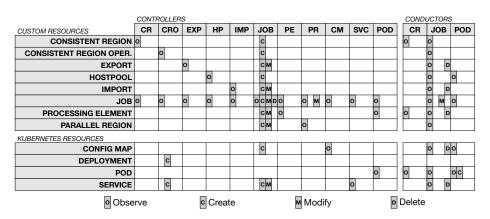


Figure 4: Clound native Streams actors and their interactions.

for the job are already running, and if they are, if the graph metadata for them has changed. If yes, then the job conductor updates the graph metadata and increments the launch count through the PE coordinator.

By composing controllers, conductors and coordinators, we construct a deterministic state machine out of an asynchronous distributed system. Controllers are state machines that react to changes on a single resource kind, but may produce changes on any resource. Conductors are state machines that react to and produce changes on multiple resource kinds. The composition of controllers and conductors is necessarily itself a state machine, but it is the addition of coordinators that makes the resulting state machine deterministic.

# 5 Architecture

Four goals guided our design:

- 1. *Discoverability*. Users should be able to use their preexisting knowledge of Kubernetes to discover what their application is doing, how to modify it, and how Streams works in general. Streams applications should also be discoverable by other workloads on the same Kubernetes cluster, through standard Kubernetes mechanisms.
- 2. *Composability*. By using Kubernetes first-class service endpoints, cloud native Streams should interoperate with other applications and middleware without further configuration.
- 3. Application state preservation. Stateless services are easy to manage in Kubernetes, as simply restarting them is always an option. But most Streams applications have state. We have an implicit contract with users that once they deploy an application, they will not lose any accumulated state—barring application failure and users taking explicit action to restart it.
- 4. Backwards compatibility. The cloud native version of Streams should run legacy Streams applications unchanged. This goal means that we cannot change any public APIs, and our task is to find the most Kuberneteslike way to express functionality originally designed for an on-premises cluster.

We also have one anti-goal: we do not maintain API com-

patibility with the legacy platform. Trying to do so would force cloud native Streams to take on responsibilities that should belong to Kubernetes, which would end up conflicting with our stated goals. We want user's *applications* to remain unchanged, but we are assuming that they are adopting cloud native Streams as part of an overall effort to consolidate and simplify management and administration.

## 5.1 Overview

All aspects of a Streams application exposed to users are represented as CRDs or existing Kubernetes resources. We apply the patterns described in § 4: each resource is managed by a controller; when we need to monitor the status of multiple kinds of resources in order to take an action we use a conductor; and when multiple actors need to change the state for a particular resource, we use a coordinator.

The CRD is the foundational unit in our design. CRDs are exposed to users in the same way as any other Kubernetes resource, which means that representing Streams concepts as CRDs gains not just native integration into the Kubernetes system, but also the user interfaces. Any state that we must maintain goes into a CRD; all state not in CRDs is ephemeral and can be lost without consequence. Kubernetes delivers reliable event notifications when CRDs and other resources are created, deleted and modified. Reacting to these notifications in controllers and conductors is the primary communication mechanism between all of the actors in our system.

The CRDs in Figure 4 define the following resources:

- Job: A single Streams job. The job controller initiates the job submission and tracks unique job identifiers. The job conductor manages the job submission process and update its status when completed.
- ProcessingElement: A PE in a job. The PE controller tracks launch count and restores voluntarily deleted PEs.
- ParallelRegion: A single parallel region in a job. It exposes a width attribute that can be directly altered by users using kubectl edit or the Kubernetes client API. The parallel region controller handles width changes applied to parallel regions.
- HostPool: A host pool in a job.

- Import: An imported stream in a job. The import controller monitors the addition and modification of these resources and matches them with export resources.
- Export: An exported stream in a job. The export controller monitors the addition and modification of these resources and matches them with import resources.
- ConsistentRegion: A consistent region in a job. The consistent region controller coordinates application checkpoints and restarts for a single region.
- ConsistentRegionOperator: tracks all consistent regions in a job. Created on-demand during a job submission with a consistent region. Its controllers monitor the deployments used to create the operators.

We also leverage the following Kubernetes resources:

- ConfigMap: Shares job specific configuration between controllers and pods, such as the graph metadata used by PEs to inform them of the operators they contain and how to connect to other PEs.
- Deployment: Manages the instance operator and the consistent region operator.
- Pod: Executes PEs. We use a pod controller to monitor and manage the life cycle of pods within jobs. The pod conductor waits until all required resources are available before starting a pod for a PE.
- Service: Exports PE entrypoints as well as user-defined services within PEs.

Figure 4 shows how our actors interact with each other. There are four kinds of actions they can take:

- 1. *observes*: the actor either receives events from Kubernetes about that resource, or passively views its store.
- 2. *creates*: the actor creates new instances of the resource through commands to Kubernetes.
- 3. *deletes*: the actor deletes particular instances of a resource through commands to Kubernetes.
- 4. *modifies*: the actor makes changes to an already created resource through that resource's coordinator.

None of our actors communicate directly with each other; all communication happens by creating, modifying or deleting Kubernetes resources.

Figure 5 depicts the deployed artifacts of an instance of cloud native Streams. The Streams *instance operator* contains all the controllers, conductors and coordinators for a Streams instance. Each Kubernetes namespace can have one Streams instance operator. The instance operator maps to the legacy concept of an instance. The legacy concept of a Streams domain—management of Streams instances—is no longer needed as the Kubernetes cluster serves that role.

In Streams, the PE is the vehicle for executing user code. PEs contain an arbitrary number of user operators and the application runtime. In our design, we always assign one PE to a pod. This design decision is fundamental. It allows us to: tie a runtime PE's life cycle to that of the pod that contains it; fully offload PE scheduling to Kubernetes; rely on the Kubernetes DNS service for establishing direct TCP

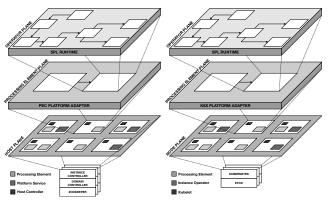


Figure 5: Legacy and cloud native Streams deployments

connections between our PEs. Any other design would have required bespoke implementations of life cycle management, scheduling and network name resolution.

While the PE runtime is unchanged, we had to implement a new translation layer between the PE and Kubernetes. It implements the platform abstraction for the PE runtime, as well as instantiates and initializes the PE. At runtime, it also: collects metrics from the PE using a pre-existing interface and exposes them to Prometheus [41]; monitors and reports the status of all PE-to-PE connections; and monitors liveness and reports it to Kubernetes.

#### 5.2 Loose Coupling

The legacy Streams platform was tightly coupled, which lead to operational difficulty and implementation complexity. Cloud native Streams applies the concept of loose coupling.

**Name resolution:** PEs communicate with each other over TCP connections. It is the platform's responsibility to define PE ports, give them names, and allow PEs to find each other's ports by those names.

In legacy Streams, each PE port is assigned a (peId, portId) tuple called a *port label* that uniquely identifies that port in the instance. At initialization, PEs must establish their remote connections to other PEs using their port labels. To that end, each PE first creates the socket receiver for each of its receiver ports, determines its local TCP port, and publishes to ZooKeeper its mapping of port label to (hostname, tcpPort). PEs already know the port label that each sending port needs to connect to through graph metadata that the platform provides at PE startup. After publishing its own receiver port labels, each PE then looks up the translation of the remote receiver port label in ZooKeeper for each of its own sender ports and establishes those connections. Even with some caching (used to reestablish lost connections), the thundering herd aspect of this initialization process and the strain it applies to the ZooKeeper ensemble delays initial deployment times.

Cloud native Streams relies on the Kubernetes name resolution system to resolve inter-PE connections. There are similarities with the legacy system name resolution system, as it relies on etcd to store its Service configurations, and it also has some currently unresolved latency issues [42, 43]. But from an application perspective, it is easier to use as name resolution is done using standard BSD functions such as gethostbyname(). Lastly, from an administration perspective, it is simpler to manage as it binds directly to the container's /etc/resolv.conf subsystem and can be easily superseded.

**Message bus:** The message bus in legacy Streams between the platform and PEs uses full-duplex, synchronous communication channels implemented with JMX [44]. All initiated communications must succeed. Failed communications are retried with increasing backoff delays before being escalated as more general system failures where it may restart a PE. As job count and PE size increases, communications tend to time out more frequently, leading to failure escalations reducing responsiveness. We have witnessed tens of minutes to list all the PEs in an overloaded instance.

Cloud native Streams decouples the instance operator from the PEs by relying on the states stored in Kubernetes to achieve operational availability. The controller pattern (§ 4.1) is used by all agents interested in keeping track of those states. Agents that need to notify the instance operator of internal state changes do so through Kubernetes events. In turn, the instance operator synchronously applies those changes to the custom resources, preventing potential race conditions (§ 4.3).

The SPL runtime, including the PEs, are implemented in C++. As of this writing, no library capable of implementing our controller pattern is available in C/C++. As an alternative, we temporarily resort to a set of REST services hosted by the instance operator. State changes within agents other than the instance operator periodically send REST operations to those services to notify the operator of internal changes. In turn, the operator applies these changes to the related custom resources. Implementing the proper library and removing the REST layer is part of our future work.

#### 5.3 Fault Tolerance and Rolling Upgrades

Fault tolerance and general high-availability is a primary goal in the design of Streams since streaming applications are expected to run for months without interruption. To that end, the legacy Streams platform was designed such that:

- 1. All platform related state is persisted in ZooKeeper. Upon failure, platform services restart and retrieve their state from ZooKeeper.
- 2. Streaming applications continue to run during platform service failures or upgrades.
- 3. Applications seamlessly resume operations after the loss of a PE or a host.

In cloud native Streams, we use Kubernetes to preserve these attributes.

**Persistent states:** Kubernetes exposes state persistence to users through CRDs. Cloud native Streams makes heavy use of CRDs to maintain states critical for recovery. However, where the legacy platform implementation favored storing the state of the system as-is, cloud native Streams stores only what is necessary and sufficient to reach the current state of the system through recomputation. The reasons behind that radical shift in the computation versus space trade-off of our system are:

- 1. We discovered through empirical measurements that the amount of time required to perform state recomputation is negligible compared to other operations in the system and appear instantaneous to human users.
- 2. Minimizing the amount of data persisted drastically reduces the pressure on the persistent ensemble.
- 3. Re-computing intermediate state simplifies the design of our system.

Instance operator: The Streams instance operator is designed to be resilient to its pod restarting. All of the actors in the instance operator will receive the full history of Kubernetes events that they are subscribed to, allowing them to catch-up to the current state of the system. The applications themselves do not need the instance operator for normal operation, so they can continue unharmed. Because of this resiliency, the instance operator can easily recover from failure. Upgrades are also trivial: change the image for the instance operator and restart the pod. The combination of how we defined our CRDs, the patterns we use to manage them and Kubernetes' reliable event delivery enable these capabilities. Applications: We consider two types of application failures: voluntary failures, when a user deletes a resource; and involuntary failures, when a PE crashes or a node becomes unavailable. The voluntary deletion of job resources are caught by the onDeletion() callback in that resource's controller. In this situation, the deleted resource is recreated by the controller if the owning job exists and is in the Submitted state.

Special care needs to be taken in the event of pod failure or PE deletion. To maintain Streams' application consistency logic ( $\S$  6.5), restarting a pod needs to be coordinated with both the PE and pod controllers through a causal chain ( $\S$  4.4).

## **6** Feature Deep-Dives

#### 6.1 Job Submission

Users submit compiled application archives to create running jobs. During job submission, the platform must:

- Create an internal logical model of the application by extracting the graph metadata from the application archive. This logical model is a graph where each node is an operator and all edges are streams. Some operators in the logical graph will not execute as literal operators, as they represent features of the application runtime.
- 2. Transform the logical model based on application features, such as parallelism or consistent regions.
- Generate a topology model from the logical model. The topology model is a graph where all of the nodes are executable operators. This process requires turning logical operators that represent application runtime features into metadata on executable operators.
- 4. Fuse the topology model into PEs. Each PE is an independent schedulable unit that contains at least one oper-

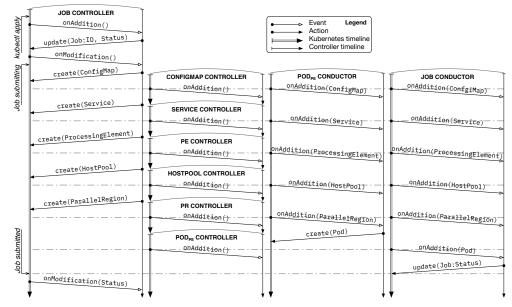


Figure 6: Job submission event diagram.

ator. Fusion also requires creating PE ports: streams between operators that cross PE boundaries require unique ports. At runtime, these ports will send and receive data across the network.

- 5. Generate graph metadata for each PE that tells it at runtime how to connect operators inside and outside of it.
- 6. Schedule and place the PEs across the cluster.
- 7. Track job submission progress.

**Legacy:** Users submitted jobs to the legacy platform through a bespoke command line tool or a development environment that communicated with the platform over JMX. This process was synchronous and monolithic. The entire process would not return until the job was either scheduled and placed, or some failure prevented that.

During job submission, PEs were given IDs that were globally unique in the instance. A PE's ports were assigned IDs that were unique across that job. Upon creation, the topology model was immediately stored in ZooKeeper. The manner of its storage was fine-grained: each node and edge was individually stored in ZooKeeper. A job's topology model, backed by ZooKeeper, was kept around and actively maintained for the lifetime of the job.

**Cloud native:** Since jobs are represented as CRDs, users submit new jobs through the kubectl apply command, or programmatically through any Kubernetes client.

Figure 6 is a job submission event diagram. Note that none of the controllers or conductors talk directly to each other: they exclusively interact with Kubernetes by creating, modifying or viewing resources. Kubernetes then delivers events based on these resources to all listening actors. When the job controller receives a new job notification, it executes steps 1– 5. The code for executing these steps is reused from the legacy platform, with three major changes: PE IDs are not globally unique in the instance, but are local to the job; PE port IDs are not unique within the job but are local to the PE; and the job topology is not stored anywhere. In fact, the job topology is discarded once the job controller extracts the metadata and stores it in a local context. Finally, the job controller assigns a job ID and marks it as Submitting by updating the job CRD.

The job controller does not create any resources for the job until it has a guarantee that Kubernetes has successfully stored the new ID and job status. It ensures this is true by waiting for the modification notification from Kubernetes. It then uses the job metadata in the local context to start creating resources. Note that this local context truly is local and ephemeral. If the job controller fails before a job is fully submitted, upon restart, it will delete the partially created resources, create a copy of the job CRD, delete the original, and create a new job through Kubernetes. It then goes through the submission process again. Rather than trying to save progress along the way, it is simpler to lose and delete transitory state and then restart the process over again.

That all actors work asynchronously is evident Figure 6's timeline. But some actions need to happen synchronously, such as pod creation: we can only create pods for PEs when we know that all of the other resources that pod depends on already exist. The conductor pattern solves this problem. The pod conductor receives creation events for all of the resources that a PE's pod needs, and only when all of those resources exist does the pod conductor create the pod for that PE.

The job conductor solves a similar problem for job status. The job submission process must report its status to users. But status is also important internally: because of the stateful nature of Streams applications, once a job has successfully submitted, simply deleting resources and starting over is no longer a viable method for dealing with updates or failures. The job conductor tracks the creation status of all resources that comprise a job, and when all exist, it commits the job to the Submitted state by updating the CRD with Kubernetes.

## 6.2 Scheduling

SPL allows users to control PE scheduling [45]: PEs can be colocated, exlocated, run in isolation or assigned to a *hostpool*, which is an SPL abstraction for a set of hosts. The platform is responsible for honoring these constraints while also scheduling the PEs across the cluster in a balanced manner.

**Legacy:** Since legacy Streams assumes that it owns the cluster, it was responsible for scheduling each PE on a host. The scheduler performs a finite number of attempts to find suitable hosts for each PE. Each round uses a different heuristic for how to favor PE placement. It tries to find a suitable host for each PE while honoring the constraints for that PE, and the constraints of the PEs already placed on hosts. The default behavior of the scheduler is to balance PEs proportional to the number of logical cores on a host while considering the PEs already placed from previous jobs.

**Cloud native:** As every PE is in its own pod, Kubernetes handles scheduling. Our responsibility is to communicate the PE constraints originally specified in the SPL application to the Kubernetes pod scheduler. The natural solution is through a pod's spec. We map the following existing SPL scheduling semantics onto the mechanisms exposed by pod specs:

Host assignment: We map the concept of a physical host in legacy Streams to a Kubernetes node in cloud native Streams. For PEs that request specific node names, we use the nodeName field in the pod spec. This mapping is natural, but requires justification: in an ideal cloud native environment, users should not need to care about what nodes their code runs on. But a use-case for legacy Streams still applies in a cloud environment: specific nodes may have special capabilities such as hardware acceleration that PEs require.

SPL also has the concept of a tagged hostpool: PEs do not request a specific host, but rather any from a set of hosts with a specific tag. The concept of tags maps directly to Kubernetes labels, which we can use with the nodeAffinity option in a pod's affinity spec.

*Colocation:* PEs request colocation with other PEs through using a common token. They don't care about what host they run on, as long as they are scheduled with other PEs that specify that token. We can achieve the same scheduling semantics using pod labels and podAffinity in the pod spec: generate a unique Kubernetes label for each token in the application, and specify that label in podAffinity in the pod spec. Together, both halves implement the full semantics: podAffinity ensures that this PE is scheduled on the same node as PEs with the same label, and the label ensures that all other PEs with matching affinity are scheduled with this PE.

*Exlocation:* PEs request exlocation from other PEs through a common token. All PEs which exlocate using the same token will run on different hosts. We achieve these semantics in Kubernetes by using the same scheme as with colocation, except we use podAntiAffinity in the pod spec.

Isolation: PEs can request isolation from other PEs, but pod specs do not have a single equivalent mechanism. However, note that requesting isolation from all other PEs is semantically equivalent to requesting exlocation from each PE individually, using a unique token for each pairing. We further note that exlocation is symmetric and transitive. It is symmetric because if two PEs are exlocated from each other, they both must have requested exlocation with the same token. And it is transitive because if A is exlocated from B, and B is exlocated from C, then A must be exlocated from C. However, the podAntiAffinity spec is not symmetric: if pod A specifies anti-affinity to B, that does not require B to specify anti-affinity to A. Because the pod relationship is not symmetric, we avoid transitivity. From this insight we can build PE isolation through pod labels and podAntiAffinity. For each isolation request in a job, create a unique label. We apply this label to each PE's pod spec, except for the PE that requested isolation. For the requesting PE, we use podAntiAffinity against that label.

## 6.3 Parallel Region Updates

SPL allows developers to annotate portions of their stream graph as *parallel regions* [46]. Parallel expansion during job submission replicates all of the operators in such regions, and the runtime partitions tuples to different replicas to improve tuple processing throughput through data parallelism.

Users can dynamically change the width of a parallel region, growing or shrinking the number of replicas. The platform will restart all PEs with operators in the parallel region, and all PEs with operators that communicate directly with them. (The PE runtime cannot dynamically its stream graph, so we must restart them to apply changes.) However, all other operators in the application should stay up. If we did not need to keep the operators outside of the parallel region running, we could trivially achieve a parallel region update by re-submitting the job with the new width and restarting everything. The process to find which operators to add, remove and modify is:

- 1. Re-generate the logical and topology model of the application with the original parallel width.
- 2. Generate the logical and topology model of the application with the new parallel width.
- 3. Perform a diff of the selected parallel region across both topology models, figuring out which operators were added, removed or changed.
- 4. Graft the target parallel region from the topology model with the new width into the original model.
- 5. Re-index all of the operators and streams in the parallel region as necessary to maintain consistency with the original topology model.

After determining the affected operators, the platform is responsible for figuring out how to add, remove or restart the PEs with them. **Legacy:** Users changed the parallel width for a region in a running job through either a command line tool or a development environment connected with the platform over JMX.

The legacy Streams platform was not designed for dynamic job topology changes. But two key design details made it particularly difficult: PE IDs are unique within the instance, and PE port IDs are unique within the job. As a result, dynamic changes cannot go through the same code path as job submissions. Trying to do so would result in assigning new IDs to unchanged PEs and ports, which would require restarting them. Instead, the legacy platform goes through a separate process for dynamic updates where only the changed operators are considered for fusion, scheduling and placement.

**Cloud native:** Kubernetes was designed for dynamic updates; updating a resource is a standard operation. We take advantage of this design because we represent parallel regions as CRDs. Users can edit the parallel region CRD's width through kubectl or a Kubernetes client. The parallel region controller will then receive the modification notification.

In cloud native Streams, PE IDs are local to the job, and PE port IDs are local to the PE. For example, if a Streams job has two PEs, their IDs are always 0 and 1. If a PE has a single input port, its ID is always 0. If a PE has *n* output ports, an additional output port will always be output port *n*. This deterministic naming also means that it is necessarily hierarchical: in order to refer to a particular PE, we must also refer to its job, and in order to refer to a particular port, we must also refer to its PE. We store this graph metadata in the ConfigMap for each PE's pod, and at runtime, PEs use this graph metadata to establish connections between each other.

This seemingly minor design point allows us to greatly simplify parallel region updates: the parallel region controller simply feeds the topology model from step 5 into the normal job submission process through the job coordinator. Our job submission process is generation-aware: each generation gets a monotonically increasing generation ID. We also do not blindly create resources, but instead use the create-or-replace model where if we try to create a resource that already exists, we instead modify it. When the parallel region controller initiates a new generation for a job, the ConfigMaps for the PEs which should not be restarted will have identical graph metadata as before, due to our deterministic naming scheme. The pod conductor remains active, even after a successful job submission. It will receive modification notifications for these ConfigMaps for each PE. If the graph metadata is identical to the previous generation, it will update the generation ID for the pod, and take no further action. If the graph metadata is different, it will initiate a pod restart through a causal chain.

### 6.4 Import/Export

SPL provides a pub/sub mechanism between jobs in the same instance through the Import and Export operators [47, 48]. These operators allow users to construct microservices out of their applications: they are loosely connected, can be updated

independently and the platform is responsible for resolving subscriptions. A common pattern we have seen in production is users will deploy an ingest application for first-level parsing. It publishes tuples through an Export operator, and various analytic applications subscribe via their Import operators. The ingest application always runs, while the analytic applications can vary from always running to quick experiments.

The three actors in this pub/sub system are:

- 1. Export operator. Publishes its input stream through a name or a set of properties.
- 2. Import operator. Subscribes to a stream based on its name or a set of properties. Stream content can also be filtered on tuple attributes using a filter expression.
- 3. Subscription broker. Part of the platform, it's responsible for discovering matches between Import and Export operators during job submission and notifying PEs to establish new connections.

**Legacy:** Upon job submission, the platform creates states for all Import and Export operators found in the job's graph metadata and stores them in ZooKeeper. It then invokes the subscription broker to compute new available routes and send route update notifications to the relevant PEs. Users can modify subscriptions at runtime either programmatically in an application through SPL and native language APIs, through a command line tool, or through dashboards. Changes are relayed to the subscription broker through the platform using the JMX protocol. Upon reception of such modifications, the subscription broker reevaluates possible import and export matches and sends route updates to the relevant PEs.

**Cloud native:** We represent Import and Export operators as CRDs. During job submission, each instance of such an operator in an application becomes a separate CRD. Users can update subscription properties by editing the CRD itself. The subscription broker is a conductor that observes events on both import and export CRDs. It maintains a local subscription board, and when it discovers a match, it notifies the relevant PE. Note that this subscription board is local state that can be lost: upon restart, the subscription broker will reconstruct it based on re-receiving all notifications from Kubernetes. The PEs ignore any redundant subscription notifications.

We replaced the JMX interface with a REST service endpoint (see § 5.2), periodically polled by the PEs to watch for changes. We replace the synchronous JMX notification with a loosely coupled UDP notification from the subscription broker to the PEs. Alterations to the import and export states from the application are also done through the REST service. This service and the import and export controllers are concurrent agents. To avoid race conditions, the REST service uses the import and export coordinators for state changes.

## 6.5 Consistent Regions

Streams provides application-level fault-tolerance through *consistent regions* [49]. A consistent region is a region of an application which guarantees at-least-once tuple processing.

The *job control plane* (JCP) periodically coordinates a consistent checkpointing protocol where operators checkpoint their local state upon seeing special punctuations in their streams. The checkpoints are stored in highly available external storage, such as RocksDB or Redis. The JCP is composed of:

- 1. A job-wide coordination system that orchestrates the consistency protocol across the job's consistent regions using a finite-state machine.
- 2. A runtime interface embedded in each PE that interacts with the coordination system in the JCP.

When a PE fails or a PE-to-PE connection drops, the JCP initiates rollback-and-recovery: failed PEs restart, all PEs instruct their operators to rollback state to the last known-good checkpoint, and sources resend all tuples whose resultant state was lost during the rollback.

Legacy: The JCP coordination system is implemented as an SPL operator [50] with a Java backend and uses a JMX message bus. Once instantiated, this operator registers itself with the platform as a JMX service endpoint. Similarly, PEs that are part of a consistent region bootstrap their JCP runtime interface at startup. This interface also registers itself as a JMX endpoint with the platform. The platform is a message broker between the JCP coordination system and the runtime interfaces of the PEs. Checkpointing is configured at the job level and the configurations are pushed to the PEs during instantiation. Each checkpointing option has a bespoke configuration system that must be determined manually by the Streams user or administrator. Life cycle events, such as PE failure, are handled by the platform and forwarded to the JCP coordination system. Lastly, the coordination system implements its own fault tolerance by storing its internal state in ZooKeeper. The storage configuration must be determined by the user and manually set as an application parameter. For instance, when using Redis, users must manually specify the names of shards and replication servers [51].

**Cloud native:** We did not change the consistent region protocols, as they are application-level. We also did not try to use Kubernetes CRDs to store operator checkpoints: they will be of an arbitrary number and size, and we wanted to maintain a clear separation between platform and application concerns.

However, we did address architectural inefficiencies by applying the loose coupling principles (§ 5.2). We moved the JCP coordination system into its own Kubernetes operator, which avoids making the instance operator the message broker between the JCP runtime and coordination system. At submission time, the instance operator creates a consistent region operator for each consistent region in a job. The consistent region operator monitors resource events through controllers and conductors. It also manages its own CRD, ConsistentRegion, used to persist internal states.

We no longer rely on a JMX message bus because Kubernetes serves that purpose: controllers and conductors receive resource event notifications from Kubernetes. The consistent region operator subscribes to pod life cycle events, PE connectivity and consistent region state change events. In the current version we use a REST service to propagate consistent region changes to PEs. PEs also use this service to notify both the instance operator and the consistent region operator of connectivity and consistent region state changes.

As an example of our composability design goal (§ 5), we automatically configure checkpoint storage. To use Redis with cloud native Streams, users specify a Redis cluster's service name. The instance operator discovers all available servers in that cluster through the service's DNS record and automatically computes the appropriate configuration.

## 6.6 System Tests

Streams relies on over 2,400 application system tests for the development and release cycle. Accumulated from a decade of product development, each test uses at least one SPL application. The tests cover integration and regression testing for all core Streams application features. They are split into two major categories: those which require the distributed platform, and those that do not. The tests which do not require the distributed platform execute the application in a single PE, running in a normal Linux process. These tests primarily focus on the correctness of the compiler, application runtime semantics, and operators from the standard library. The tests which do require the distributed platform test many of the application features covered in this paper: PE-to-PE communication, metrics, consistent regions, parallel regions and any sort of application behavior which requires non-trivial interaction with its external environment. The test which require the distributed platform use multiple PEs (up to hundreds) and some use multiple SPL applications.

Tests are organized in scenarios containing a list of steps to perform, environment variables to use, and context tags to honor. Context tags are descriptors used by the test harness driver to determine the appropriate node the test must run on, attributes such as the operating system version or whether the node must be equipped with a network accelerator.

A variety of test steps are available, ranging from moving files around to randomly killing critical processes. Test success or failures are determined using special steps called probes that wait for the system to reach a particular state to complete, such as waiting for a job to be in the Submitted state, or waiting for all the processing elements of a job to be in the Connected state.

**Legacy:** In order to operate with legacy Streams, our system test framework must be pre-installed on the target cluster. The target node names must be known and collected in the framework's configuration files. The cluster must also have a specific file system layout and sharing configuration in order for tests expecting shared files to operate. The version of IBM Streams being tested must be available at the same place in the file hierarchy to all nodes in the cluster. If the test application writes or reads files, those files must be available over a Network File System. **Cloud native:** Similar to our platform itself, we organize the system we use to test it around Kubernetes operators and CRDs. We define a TestSuite CRD which maintains five lists of tests: pending, running, passed, failed and aborted. It also maintains testing parameters such how to select tests to run, how many tests to run concurrently, how many failures to tolerate before stopping a run, and what to do with testing artifacts. Users initiate a new test run by creating a TestSuite CRD which specifies which tests to run. The TestSuite controller will select N tests to go on the running list, where Nis the concurrency number. The remaining tests that meet the selection criteria go on the pending list. The TestSuite controller then creates a pod for each test on the running list. When a test pod finishes, the pod controller uses a TestSuite coordinator to indicate test success or failure. The coordinator computes how the test lists should be modified, creates a new pod for the next test on the pending list, and finally updates the CRD itself to match the computed test lists. This process repeats until the pending list is empty, or the failed and aborted list exceed the failure threshold.

The TestSuite controllers run in a test harness Kubernetes operator. This test harness architecture enjoys all the benefits of being cloud native. It can run on any Kubernetes cluster; it does not require any system-specific configuration except node labels to expose available hardware accelerators; it makes testing for a specific operating system version irrelevant as both cloud native Streams and the test framework are distributed as container images; it makes test run completely discoverable through the use of the TestSuite CRD; it is resilient to failures because all important state is stored in the CRD; and test runners and test executions can be monitored like any other pods in the cluster with standard tools like Prometheus and Grafana. Finally, the harness operator is blind to the kind of test runners it creates as from its perspective it only manipulate pods and their execution states.

## 7 Lessons learned

During design, implementation and testing, we adopted lessons that served as general guidance:

- 1. Don't store what you can compute. Storing state in a distributed system is expensive—not just in bytes and bandwidth, but in complexity. Modifying that state requires transactions and forces components to synchronize. This complexity will necessarily infect the rest of the system. If it is possible to recompute a result, the cost in cycles buys a simpler design.
- 2. Align your design with Kubernetes concepts. Alignment enables integration and simplification. We did not have to implement any management of Streams instances in cloud-native Streams because we enforce one Streams instance per Kubernetes namespace. In legacy Streams, a domain managed multiple instances. We get that for free as our "domain" just becomes the Kubernetes cluster.
- 3. Don't re-implement what Kubernetes already provides.

The value in using a general purpose distributed platform is not having to re-implement the basics. Designs which require implementing bespoke versions of life cycle management, communication, storage or configuration not only waste code and effort. Such designs are also less likely to integrate well into Kubernetes, forcing even more bespoke implementations of other features.

- 4. *Rely on Kubernetes for atomicity, consistency and redundancy.* Kubernetes provides reliable storage, and sends totally ordered, reliable notifications based on changes to the objects in that storage. Building systems using these primitives allows for simpler, better integrated designs.
- 5. Always use hierarchical, deterministic naming. Globally unique names in a distributed system are a form of state: creating them requires synchronization to avoid duplicates, and their metadata must be durably stored. For top-level objects in a system, this property is unavoidable. But named objects nested in those top-level objects do not need to be globally unique, as their top-level object is an implicit namespace. Requiring such nested names to be globally unique imposes unnecessary state management and synchronization. Hierarchical, deterministic naming schemes allows other entities in the system to *compute* what the names must be.

# 8 Results

## 8.1 Experimental results

Raw performance was not a motivation (§ 3.3) or design goal (§ 5). However, if cloud native Streams' platform performance was significantly worse than legacy Streams', then it would not be an acceptable replacement. The primary goal of our experiments is to demonstrate that cloud native Streams has acceptable comparable performance, and the secondary goal is to identify aspects of Kubernetes which can be improved.

We ran our experiments on a 14 node cluster using Streams v4.3.1.0 as legacy, Kubernetes v1.14 and Docker v18.09.6. Each node has two 4-core Intel Xeon X5570 processors at 2.93 GHz with hyperthreading enabled and 48GB of memory. One node is dedicated to management, leaving 13 nodes and 104 physical cores (208 logical cores) for applications.

Unless otherwise stated, our test application has a source operator which continuously generates tuples and feeds into an *n*-way parallel region. Each channel in the parallel region has a pipeline of *n* operators, and all channels eventually converge into a sink operator. We fuse each operator into its own PE. We vary *n* in our experiments, which means that the number of operators and PEs grows with  $n^2$ . As described earlier, each PE is a separate process and runs in its own pod. Different experiments need a different number of pre- and post-processing operators before and after the parallel region. **Job life cycle:** The three job life cycle phases exposed to users are submission, full health and full termination. The submission time is how long it takes for the platform to create all of the PEs and job resources. Such jobs are still initializing

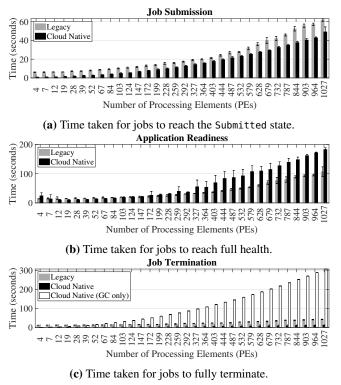


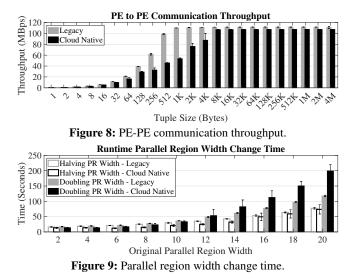
Figure 7: Job life cycle times.

and are not yet processing data. Only when all PEs are running and have established all connections is the application processing data and considered fully healthy. Finally, after the user cancels the job, the platform considers the job fully terminated after all PEs and associated resources are gone.

Figure 7 shows how long it takes to reach each phase of the job life cycle for both cloud native and legacy Streams, with each data point representing the average of 10 runs. Figure 7a shows that cloud native Streams is consistently faster to reach the Submitted state. Reaching the Submitted state only requires resource creation; for legacy Streams, that means registering all resources in ZooKeeper, and for cloud native Streams that means all resources are stored in etcd. However, legacy Streams also computes PE schedules: it rejects jobs for which it cannot find a valid schedule. In cloud native Streams, Kubernetes schedules PE's pods asynchronously.

The time it takes for cloud native Streams to reach full health, Figure 7b, is dependent on whether the cluster is oversubscribed. Each PE is a process in a separate pod, and the experiments scale to 1027 PEs. But the cluster will be fully subscribed by at least 208 PEs; there are more processes than cores. Before the cluster is fully subscribed, cloud native Streams performs competitively with legacy Streams. Both versions suffer as the cluster becomes more oversubscribed, but cloud native Streams eventually takes twice as long.

The job termination experiments, Figure 7c, have results for two different approaches for cloud native Streams: manual resource deletion and relying on Kubernetes' garbage collector. In the case of manual deletion, the job controller actively



cleans up by telling Kubernetes to delete resources in bulk by their label. Bulk deletion minimizes the number of API calls and therefore reduces the strain on Kubernetes' API server. We originally relied on Kubernetes' resource garbage collector to automatically reclaim resources owned by deleted jobs. Kubernetes' garbage collector, however, does not scale well as the number of resources grows.

**PE-to-PE communication throughput:** The experiments in Figure 8 use an application designed to test PE-to-PE throughput. It consists of two PEs, pinned to two fixed nodes in our testbed, while varying the size of the tuple payload from 1 byte to 4 MB. Transmissions run for 5 minutes, with throughput measurements every 10 seconds.

Cloud native Streams achieves significantly lower throughput than legacy when the tuple size is smaller than 4 KB. This performance degradation is due to the deeper networking stack used within Kubernetes. Because of its networking architecture, a single packet sent from one container is required to cross various virtual interfaces and packet filters before reaching another container. Comparatively, a packet sent between two PEs within the legacy Streams platform is directly sent to the default interface for the target route. This increased complexity has the most pronounced effect with payloads less than 8 KB. With larger payloads, the increased networking cost is mostly amortized.

**Parallel region width change:** Figure 9 has two sets of experiments: increasing and decreasing parallel region width. The *x*-axis is the starting width of the parallel region, and we measure how long it takes an application currently at full health to either double or halve that parallel region. In general, cloud native Streams benefits from the concurrency enabled by the design from § 6.3. Starting new PEs and terminating the old PEs happens concurrently, handled by Kubernetes' pod scheduling. In legacy Streams, these phases need to happen sequentially. Cloud native Streams also has less communication with its metadata backing store (etcd) than legacy Streams (ZooKeeper). Starting at a width of 12, the

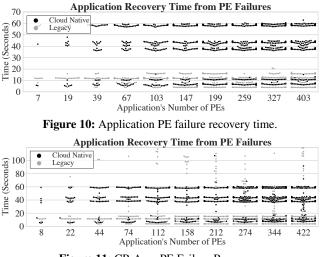


Figure 11: CR App. PE Failure Recovery.

cluster is oversubscribed (the number of PEs grows with the square of the width). At that point, when doubling the width, we see the same behavior regarding starting new PEs in an oversubscribed cluster as in Figure 7b.

**PE failure recovery:** We test PE recovery time in Figure 10. The *x*-axis is the number of PEs in the application, and each dot represents how long it took the application to return to full health after we killed a particular PE. This process times how long it takes for the platform to detect that the PE is gone, start a replacement, and wait for the replacement PE to re-establish all connections. The clustered times are due to different PEs being in similar places in the application topology. In cloud native Streams, the delay is in re-establishing the connections; the PEs are restarted quickly as that is almost entirely handled through Kubernetes' pod management.

**Consistent region PE failure recovery:** The experiments in Figure 11 are the same as in the PE failure recovery with the addition that the operators are also in a consistent region. This addition means that their recovery is managed by the consistent region protocol (§ 6.5) which requires more communication and coordination than just restarting the PEs. The outlier latencies tend to be the PEs which have more connections.

**Discussion:** One benefit of a bespoke platform is specialization. Our experimental results show that there is currently a cost for some actions when using Kubernetes as a generic platform. Improving these parts of Kubernetes will improve its ability to handle workloads such as Streams.

*Oversubscription:* Cloud native Streams behaves poorly compared to legacy Streams when the cluster is oversubscribed. We have identified two potential culprits. First, the DNS propagation in Kubernetes seems to be slower than the name resolution mechanism in legacy Streams. This latency is likely caused by the extra complexity of pod networking. Second, many more subsystems are involved in cloud native Streams than legacy Streams when creating new PEs:

where fork() is enough for the latter, the former calls upon the Docker daemon and various Linux kernel facilities such as cgroups to start new pods.

*Networking latency:* The increased latency is the biggest pain point as IBM Streams was designed and engineered as a low latency, high throughput streaming solution. This is especially true as the most common tuple size used by Streams customers is around 500 bytes, within the size range where the latency degradation reaches 50%. A solution is to use two different planes for control and data: Kubernetes networking for the Streams control plane, while a separate network for the Streams data plane. Such a separation can be achieved through user-space networking, either through a bespoke user-space TCP/IP network stack integrated into Streams' runtime or through a Kubernetes plugin supporting user-space networking, such as Microsoft FreeFlow [52].

*Garbage collector:* When handled completely by the Kubernetes garbage collector, our resource deletion time experienced significant latency even with a modest number of resources on an undersubscribed cluster. The garbage collector could likely be tuned to reduce the deletion time, but such tuning introduces the danger of overfitting it to one specific workload at the detriment of others. Garbage collector plugins similar to scheduler plugins could solve this problem.

PE recovery: We initially suspected the container runtime added latency, but further investigation conducted by stressing container creation and deletion did not show any behavior that would explain the increasing recovery latency past 100 PEs. Another intuition concerns the networking address allocation for PEs: when recovering a failed PE, the legacy Streams platform will respawn the process on the same host. By doing so, the name resolution stays stable and other PEs communicating with the respawned process will be able to reconnect to it immediately. However, on the Kubernetes platform, PEs may not end up with the same container IP address, even when allocated on the same host. Therefore, all PEs communicating with the respawned process first need to get a fresh name translation record, which is dependent on how fast the Kubernetes DNS subsystem propagate changes. Validation requires more investigation. However, some workloads may benefit from stable IP addresses for pods. Such stable addressing could be implemented by either updating an existing network plugin or implementing a network plugin specific to the workload.

### 8.2 Lines of Code

Rearchitecting a legacy product to be cloud native should offload significant responsibility to the cloud platform. This process should significantly reduce the lines of code in the implementation. Table 1 shows that reduction.

	legacy	cloud native
SPL	429,406	415,809
platform	569,933	148,375
install	14,785	0
total	1,014,124	564,184

Table 1: Physical lines of source code across Streams versions.

We use scc [53] to count code. It counts physical source lines of code, which is defined as lines of code which are not comments or blank. The languages included in our count are C++, Java, Perl, XML Schema and YAML. The SPL compiler is primarily C++, with some of the user-exposed code generation features in Perl. The SPL runtime is split between C++ and Java. The legacy platform is about 80% Java, 20% C++. The install is primarily Java. We do not include code related to the build process or system tests.

Cloud native Streams is about half the size of the legacy version, and the platform is about a quarter the size of the old platform. The implementation of the architecture presented in this paper is about 26,000 lines of code, which means that we reused about 122,000 lines of platform code. Most of that code is the job submission pipeline (§ 6.1). The cloud native version does not have an installer: users apply the YAMLs for the CRDs and make the Docker images available which contain the instance operator and the application runtime.

# 9 Conclusion

Cloud native Streams replaces the IBM Streams platform with Kubernetes. It offloads life cycle management, scheduling, networking and fault tolerance to Kubernetes. It does this by using Kubernetes as a state-management-service: all important state is managed by Kubernetes, and its services react to state change events delivered by Kubernetes. Those services implement the cloud native patterns presented here: controllers, conductors, coordinators and the causal chains formed by their interactions. Other workloads can use these patterns to implement their own cloud native platforms. We have also experimentally demonstrated areas in which Kubernetes needs improvement to better serve as a generic platform: performance in an oversubscribed cluster, networking latency, garbage collector performance and pod recovery latency.

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