Binge: Processing All of the Things with a BINary-at-the-EdGe

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Abstract

Most stream and event processing is done using popular Stream Processing Engines (SPE), such as Apache Storm, using event-based design patterns within a custom application stack, or a combination of the two. In either case, the foundation of these architectures relies on a centralized event bus or pub/sub system that acts as a buffer for processing events. While this approach is well understood and ubiquitous, it is not well-suited to many current and future applications within edge computing and modern SaaS applications. While there will likely always be a need for centralized event buses and custom application stacks, a great deal of stream processing can be done without an SPE or core application stack.

In this paper, we present Binge (binary-at-the-edge), a lightweight, durable, scalable, stream processing daemon that can run on commodity hardware without the need for complex application and infrastructure configurations. Each binge instance only relies on its own local configuration, which allows it to scale horizontally and heterogeneously. We show that binge can be leveraged for simple stream processing tasks at the IoT edge, VPC edge, PoP edge and as a mesh of coordinating endpoints.

1 Introduction

The ubiquity of software-as-a-service (SaaS) (e.g., Salesforce, Slack, GitHub, etc.) and cloud platform services (PaaS) (e.g., AWS, Google Cloud and Azure) has created a complex ecosystem of integration platforms that integrate SaaS services via events and APIs. There are a great deal of products aimed at automating decision making, tracking customer experience, automating engineering processes, and so on. These products are effectively consuming event data from SaaS services and processing it in managed PaaS services. Integrating with a SaaS platform typically means subscribing to events, consuming events and calling their APIs. A basic integration platform may consume all events from any number of SaaS integrations and publish them to Kafka topics to be consumed by SPEs, custom microservice applications or big data systems such as BigQuery.

The many emerging IoT use cases are very similar. That is, consuming disperate events, publishing them to a centralized event bus and using SPEs to process. The main difference between the IoT use cases and the integration platform use case is the definition of edge. In the case of IoT, the edge is as close to the devices as possible, while the integration platform is usually a point-of-presence (PoP) or a load balancer in the platform's VPC or data center. In each case, there are different assumptions around what resources are available. For example, it might not be safe to assume now-latency access to a Kafka broker in the IoT use case, but the integration platform edge may be on the same network as a Kafka cluster. In the most ideal case, all filtering, transformation and processing can be done as close to the edge as possible. In reality, most of this is still done in a centralized fashion, albeit in distributed SPEs and microservice architectures.

The goal of binge is to simplify moving as much event processing as possible to the edge (depending on what edge means for the application) in a way that is durable, flexible and easy to operate. The goal is not to usurp existing SPEs or event based architectures, but to compliment them in a way that performs processing in the most appropriate tier (edge vs. hub) depending on cost, resources, performance, etc.

2 Outline

The remainder of this article is organized as follows. Sections 3 and **??** cover the design and implementation of Binge. We go through a few potential use cases for using Binge in Section **??**. We evaluate the performance of Binge in Section **??**. Section **??** gives account of previous work. Finally, Section **??** covers future work and we conclude in Section **??**.

3 Binge Design

The high-level components of Binge are illustrated in Figure 1. Opposed to most SPEs and microservice architectures, which require a great deal of configuration and moving parts, Binge is composed of a single binary that can run as a command (e.g. process a single event in a Lmabda for use in a serverless architecture, for testing or debugging) or as a daemon. The figure shows the components used for daemon mode. Binge exposes a HTTP endpoint that accepts POST requests containing JSON-formatted content, each representing an event. All events consumed by the daemon are persisted to a durable queue, which are consumed by workers. Each event will be processed by a worker in one or more pipelines defined in the configuration. Once a worker has completed processing an event, it will ack the event and pick up more work. This in combination with checkpointing (discussed later) allows the each daemon to be killed without losing events or processing state. Later we will discuss tradeoffs with the various durability configurations.

Today, the daemon can be also be configured in stateless mode, which disables the durable queue.

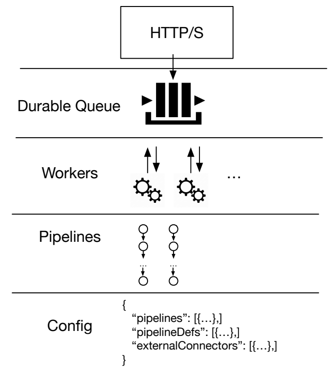

Figure 1: This

This configuration can be used in cases where reliable delivery is less important than performance. In addition, there are some use cases where HTTP is not a sufficient interface. Adding new endpoint interfaces is relatively easy. For example, we can create a consumer interface that consumes messages from MTTQ queues when running in an IoT edge. The only difference here is that the daemon operates in a pull model opposed to the push model of an HTTP endpoint.

The rest of this section will be devoted to digging deeper into the durable queueing mechanism, pipelines, configuration and tradeoffs between different configurations.

3.1 Durable Queue

All events posted to the binge daemon are immediately placed into a durable queue before replying with success to the caller. This is done for two reasons. First, it allows this or another daemon to process events that were either unprocessed or in-flight after a crash. Second, it provides a buffering mechanism between the incoming events and the workers, preventing the need to apply backpressure. The remainer of this section is devoted to both of these aspects of the durable queue.

3.1.1 Event Processing and Crashes

The durable queue maintains three buckets: in-flight, unprocessed and an internal bucket for queue metadata, such as head and tail location of the unprocessed events. Figure 2 shows the basic data structures and a simple example. The queue can technically be backed by any underlying data structure that implements the following interface:

```
type DQueue interface {
    Dequeue() (*QueueItem, error)
    Enqueue(v []byte) error
    Ack(*QueueItem) error
}
```

We currently rely on BoltDB (https://github.com/etcd-io/bbolt) for persistence. Swapping out backends is trivial as long as the backing system can be mapped to a Key-Value interface. We chose BoltDB because it is fast, stable and runs in-process, which allows us to minimize the number of external dependencies. Running BoltDB also allows for configurations to easily leverage external block stores for persistence, which lends itself to more ephemeral environments.

As shown in Figure 2, we have 5 unprocessed events a 0 in-flight, before a worker pulls an event off the queue. Prior to returning the event to the worker, Evt_3 is atomically swapped to the in-flight queue. An event is not removed from the in-flight queue until it is acked. While processing the event, the daemon (as well as the worker) crashes and restarts. Before accespting any new connections the daemon will process the unprocessed and in-flight queues. Depending on the current status of each event, some may remain on the in-flight queue after the start-up process finishes. This could be due to an external resource being unavailable or an issue with the state of the event or checkpoint. The proper action depends mostly on the use case and could be a combination of: throw the events away, fire an alert, or forward the events to another system [1]

The self-contained nature of binge also allows many instances to serve the same event streams where daemons fail and recover without direct coordination. For example, if running in Kubernetes, a binge pod can be bounced and will simply continue using the same persistent volume when it restarts. We get similar behavior when running in VMs or on physical hardware, provided a supervisor detects the daemon stopped and requires restart.

[1]ToDo: Add recovery rules to the pipelines. For example, add an OnFail section to a process, which can take an action when it fails

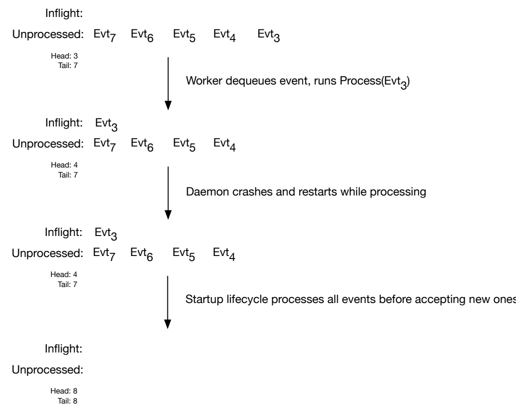

Figure 2: This

3.1.2 Backpressure

We want to ensure all events are eventually processed, but there are times when a daemon gets overloaded and applies backpressure, usually in the form of a HTTP 429 response. One way to avoid the need to apply backpressure is to put a buffer between the enpoint serving the request and the processing. Here, the tradeoff is that returning a 200 OK only means the event has been persisted and the event is hopefully processed. As we have shown, we use a durable queue as our buffer. We use tracing to ensure we have visibility into the state of all events.

Given that binge may be running in a resource constrained environment, it is possible that a daemon is overloaded and the queue exhausts disk space in either a local or remote volume. There are two complimentary ways to ensure events are not lost: spin-up more instances (if possible) and/or specify high-water marks used to offload the latest events to an external system until a low-water mark is hit and we can pull those events in [2].

In the worst case, the daemon is running in a resource constrained environment, runs out of disk space and eventually has to resort to backpressure. In any case, the daemon itself can be configured to mitigate this issue by offloading newly consumed events until a low-water mark is hit.

3.1.3 Stateless Mode

As previously discussed, binge can run in stateless mode, either as a daemon or in command mode. Stateless mode effectively disables the durable queueing mechanism and crash recovery lifecycle. This means that backpressure will be applied when the all of the daemon threads or allowable connections are consumed, and unprocessed events will likely be dropped in the event of a crash.

This mode is best suited for cases where the source events can be safely dropped or binge is run within a serverless architecture (i.e. command mode). As we will show in the next section, pipelines provide a checkpoint mechanism that can ensure indivdual pipeline executions can proceed after a crash.

3.2 Pipeline Processes

Pipelines are at the heart of binge. Each event will be proceessed through every pipeline configured for the daemon. This allows different binge/configuration artifacts to be deployed for specific events. For example, you can deploy a specific configuration to an auto-scale group to serve events for your CI/CD processes from GitHub, GitLab and CircleCI, while a separate configuration is deployed to an auto-scale group to serve your Slack events.

A pipeline is a colleciton of processes that are applied in sequetial order. Each process must implement the following interface to be used within a pipeline:

```
type PipelineProcess interface {
	Process(ctx context.Context, in map[
		string]interface{}) (map[string]
		interface{}, error)
}
```

The context is used to plumb contextual information through the pipeline, the individual processes and onto external dependencies, such as Key-Value Stores. As we will see the pipelines can be configured to automatically add OpenTelemetry [?] trace context to select requests.

At a high level, the Process function takes in a map and outputs a map. The source can be any structured data format that can be converted into a map, such as JSON, YAML, CSV, protobuf, etc. As we will see, this simple abstraction allows one to define a rich set of operations that can handle many stream processing tasks.

Each pipeline invocation will process an event serially through the pipeline. We rely on a $Completable/Future$ abstraction, which simplifies asynchronous processing. Since Golang does not have native support for $Futures$, we created our own implementation. In a nutshell, a *Completable* contains the eventual result of a computation, which is exposed to the caller as a $Future$. The caller can invoke $Future.Get()$ to block and obtain the result, or rely on callbacks to perform actions on the result. To enable highly concurrent pipelines, the Future abstraction exposes a $Then(Runnable)$ function that will run the provided runnable using output of the parent future as input, when the parent future completes. This model maps very nicely with invoking pipelines on events.

Figure 3 illustrates how the Future abstraction fits nicely with pipeline invocation. Each pipeline process is contained in a runnable object. A $RunnableStartProcess$ must implement $Run()$, which will simply invoke $Process$. A $RunnablePartialProcess$ must implement both Run and $SetInData$, where $SetInData$ is called by $Then$ with the result of the previous future and Run invokes $Process$ with the result.

In addition to chaining, callbacks such as Prepare, OnSuccess and OnFailure are used to add instrumentation (meters and counters) and trace information (spans) to the individual processes.

[2]ToDo: This can be worked into the configuration, likely as a command line option for the daemon

```
// RunnableStartProcess will create a runnable
    that calls
// outMap = pipelineProcess1.Process(inMap)
runnable1 := NewRunnableStartProcess(
    pipelineProcess1, inMap)

// RunnablePartialProcess will create a runnable
    that implements
// SetInData(x map[string]interface{}) and runs
    pipelineProcess2.Process(SetInData(x))
runnable2 := NewRunnablePartialProcess(
    pipelineProcess2)
runnable3 := NewRunnablePartialProcess(
    pipelineProcess3)

// A pipeline invocation is a chain of futures
f1 := CreateFuture(runnable1)
f2 := f1.Then(runnable2)
f3 := f2.Then(runnable3)
f3.Get()
```

Figure 3: Example of chaining runnables

3.3 Pipeline Configuration

There are five manjor components to a pipeline configuration:

- **External Systems:** This contains global configuration for external systems, such as databases, key-value stores, SPEs, HTTP/gRPC endpoints or pub/sub systems.
- **Pipeline Process Definition:** This contains the configuration for a pipeline process that can be referenced by one or more pieplines.
- **Pipeline Manifests:** Each pipeline will contain a manifest, which is a list of ordered pipeline processes that define the pipeline.
- **Checkpoint Process:** The checkpoint process is a special process that will checkpoint state to a provided external system. It is configured per pipeline.
- **Pipelines:** Pipelines is root configuration object for binge and contains the external systems, pipeline process definitions and pipeline manifests.

3.4 Pipeline Process Types

As shown in Table **??**, there are seven process types. As described in Section 3.2, a process essentially processes an input map and returns an output map. Many of the processes can be conditionally guarded with a condition implementing the folloowing interface:

```
type Condition interface {
   Evaluate(in map[string]interface{}) (bool,
       error)
}
```

A condition is applied to the input map, where the target process will run if and only if Condition evaluates to true. An error will either lead to failure of the pipeline run for this event or will invoke the error handler specified in the process definition.

All but two of the processes apply updates to the map. Note that the input map left untouched and an update simply means the output map is a transformed copy of the input map.

The Annotator, Filter and Spawner are the simplest of the processes, and all can be defined with a conditional guard. An Annotator will simply add annotations to the map. A Filter will either apply a filter or inverse filter to a map. Finally, a Spawner will spawn a job. Currently, jobs are processes that are spawned locally must adhere to the same interface a Processes. That is, a JSON-encoded map is written to standard input and a JSON-encoded map is expected on standard output.

The remaining processes require more explanation and we will spend the rest of this section describing them with a few examples.

3.5 Aggregator

An Aggregator exposees many common aggregations provided by SPEs and databases. Currently, we support Sum, Max, Min, Avg, Count and Histograms. An Aggregator is defined by 4 components:

Type	Desc	Cond?	Update?	Stateful?
Annotator	Add annotations to output map	Yes	Yes	No
Aggregator	Update an aggregation based on one or more fields	Yes	Yes	Yes
Completor	Define a join on N fields and emit a completion annotation when a specific value for all N fields is observed	No	Yes	Yes
Filter	Filter (or inverse filter) fields using string match or regex	No	Yes	No
Spawner	Spawn a job	Yes	No	No
Transformer	Transform one or more fields of the source map	Yes	Yes	No
Tee	Send the current map or a transformed map to an external system	Yes	No	No

Table 1: Process types

- **State Store** This specifies the external system used to store the aggregation, which can be anything from a local file system to an external key-value store.
- **Field Key** This is the field key that corresponds to the value to aggregate.
- **Aggregation Type** This is the type of aggregatioon to apply.
- **Group By** Group by applies to all but the Histogram aggregation and will aggregate by the keys provided.

Figure **??** shows an example snapshot of a pipeline run containing three aggregation processes. First, we see the output map of the previous process passed into the Sum aggregation. The Aggregator process will try to fetch state for this aggregation. If there is no state, it will create new state. In either case, a new annotation is added to the map containing the current state of the aggregation after it is updated. These annotations can be used by downstream processes to conditionally run processes, to further aggregate or make other decisions. The figure also illustrates the use of histogram aggregations and a simple count.

This example also highlights another well-known issue with stateful stream processes: tracking consistent state. There are three main tradeoffs that arise with respect to stateful processes:

- **Consistency** Maintaining consistent state requires coordination or centralization.
- **Performance** Requiring consistent stateful processes will negatively impact latency.
- **Starvation** Requiring consistent stateful processes could lead to starvation.

There are two modes of operation here:

- Use a centralized key-value store to maintain state. At minimum we would want atomic put and delete to ensure consistency.
- Rely on a local persistent store (file system or local key-vallue store) and aggregate the aggregations at a binge sink that is close to a centralized key-value store.

The first option is the easiest to reason about, since we simply specify an external system to use. The major cloud providers have a variety of options that can be deployed at the push of a button. Here, the conceern is performance: increase in latency due to round-trip time and contention. Contention could be mitigated using higih-performance key-value stores, such as Anna [**?**]. In either case, the distance between the binge process and the centralized key-value store will largely dictate the performance overhead.

The second option relies on the existance of a binge-mesh, where a pipeline maintains local aggregation state and relies on a downstream binge process to perform the final aggregation. In this case, the final aggregation could be performed closer to a centralized key-value store. Note that here the round-trip time doesn't change, but our throughput will likely be higher than the first option. The main disadvatage to this approach is managing the mesh of binge processes. We will cover this in Section **??**.

4 Binge Implementaion

5 Orchestration

6 Example Use Cases

7 Performance Evaluation

8 Previous work

9 Limitations and Future Work

10 Conclusions

We worked hard, and achieved very little.

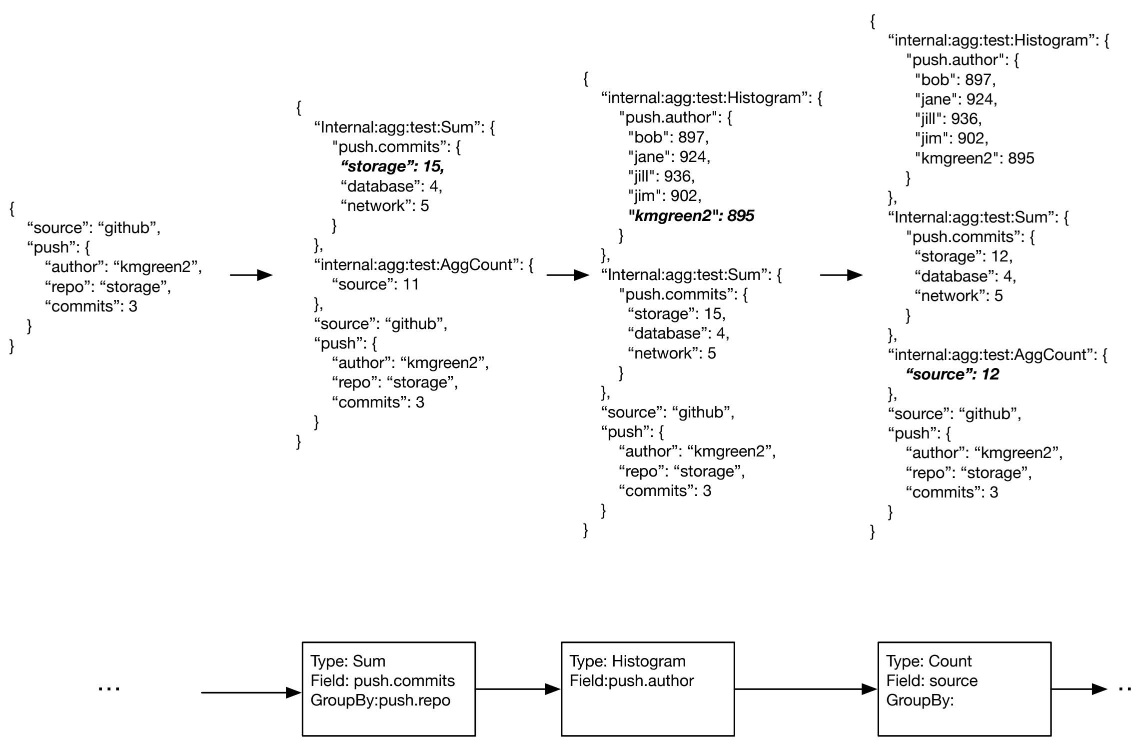

Figure 4: Figure