# Pilot-Streaming: A Stream Processing Framework for High-Performance Computing

Andre Luckow
Ludwig-Maximilians-University and
Rutgers University
Munich, Germany
andre.luckow@ifi.lmu.de

George Chantzialexiou Rutgers University Piscataway, NJ georgeha98@gmail.com Shantenu Jha Rutgers University and Brookhaven National Laboratory Piscataway, NJ shantenu.jha@rutgers.edu

## **ABSTRACT**

An increasing number of scientific applications rely on stream processing for generating timely insights from data feeds of scientific instruments, simulations, and Internet-of-Thing (IoT) sensors. The development of streaming applications is a complex task and requires the integration of heterogeneous, distributed infrastructure, frameworks, middleware and application components. Different application components are often written in different languages using different abstractions and frameworks. Often, additional components, such as a message broker (e.g. Kafka), are required to decouple data production and consumptions and avoiding issues, such as back-pressure. Streaming applications may be extremely dynamic due to factors, such as variable data rates caused by the data source, adaptive sampling techniques or network congestions, variable processing loads caused by usage of different machine learning algorithms. As a result application-level resource management that can respond to changes in one of these factors is critical. We propose Pilot-Streaming, a framework for supporting streaming frameworks, applications and their resource management needs on HPC infrastructure. Pilot-Streaming is based on the Pilot-Job concept and enables developers to manage distributed computing and data resources for complex streaming applications. It enables applications to dynamically respond to resource requirements by adding/removing resources at runtime. This capability is critical for balancing complex streaming pipelines. To address the complexity in developing and characterization of streaming applications, we present the Streaming Mini- App framework, which supports different plug-able algorithms for data generation and processing, e.g., for reconstructing light source images using different techniques. We utilize the Mini-App framework to conduct an evaluation of the Pilot-Streaming capabilities.

## **KEYWORDS**

Streaming, HPC, Big Data

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HPDC'18, 2018

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#### **ACM Reference Format:**

Andre Luckow, George Chantzialexiou, and Shantenu Jha. 2018. Pilot-Streaming: A Stream Processing Framework for High-Performance Computing. In *Proceedings of ACM The 27th International Symposium on High-Performance Parallel and Distributed Computing, Tempe, Arizona, USA (HPDC'18)*. ACM, New York, NY, USA, 12 pages. https://doi.org/

## 1 INTRODUCTION

Stream processing capabilities are increasingly important to analyze and derive realtime insights on incoming data from experiments, simulations, and Internet-of-Things (IoT) sensor [16]. For example, the National Synchrotron Light Sources II (NSLS-II) is projected to generate data at a rate of 20 GB/sec [8]. For many beamlines, this data needs to be processed in a time-sensitive if not real-time manner, to support steering of the experiments [3]. Further, an increasing number of scientific workflows integrate simulations either with data from experimental and observational instruments, or real-time analytics of simulation data [36]. Such workflows are stymied by the fact that capabilities to continuously process time-sensitive data on HPC infrastructures are underdeveloped while they require sophisticated approaches for resource management, data movement and analysis.

The resource management capabilities provided by Pilot-Jobs [34] have proven to be effective in supporting task-level parallelism on HPC machines. In previous work, we demonstrated the use of Pilot-Jobs to manage big data frameworks on HPC environments [21, 32]. In this paper we propose *Pilot-Streaming*, a framework designed to efficiently deploy and manage streaming frameworks for message brokering and processing – such as Kafka [26], Spark [54], Flink [5] and Dask [10], on HPC systems. We argue that the complex application and resource utilization patterns of streaming applications critically demand dynamic resource management capabilities as provided by Pilot-Jobs. For example, minor changes in data rates, network bandwidth, processing approach can lead to backpressure and a dysfunctional system. Pilot-Streaming provides the ability to overcome these problems by efficiently supporting the resource management needs of streaming frameworks and applications. Further, Pilot-Streaming serves as unifying layer for managing computational tasks in an interoperable, framework-agnostic way.

Developing streaming applications is a complex undertaking as they typically consist of multiple dependent components: data source, message broker and typically multiple stages of processing components. Often, these streaming pipelines cannot be developed with direct access to the production data source. Based on a systematic analysis of different scientific streaming application, we

develop the *Streaming Mini-Apps* framework to addresses these critical gaps. The framework provides the ability to quickly develop streaming applications and to gain an understanding of the performance of the pipeline, existing bottlenecks, and resource needs. We demonstrate the capabilities of Pilot-Streaming and the Streaming Mini-App framework by conducting a comprehensive set of experiments evaluating e.g. the processing throughput of different image reconstruction algorithms.

This paper makes the following contributions: (i) it surveys the current state of message broker and streaming frameworks with respect to their ability to support scientific streaming applications. (ii) It provides a conceptual framework for analyzing scientific streaming applications and applies it to a machine learning and light source analytics use case. (iii) It presents a normative architecture for stream processing frameworks on HPC. Pilot-Streaming is a reference implementation of that architecture. (iv) It demonstrates the capabilities of Pilot-Streaming and the Streaming Mini-Apps using a set of large-scale experiments on the XSEDE machine Wrangler, for streaming machine learning and different light source reconstruction algorithms.

This paper is structured as follows: In section 2 we investigate the architectural components of a typical streaming infrastructures and applications and related work. We continue with an analysis of streaming applications in section 3. Section 4 presents the architecture, capabilities and abstractions provided by Pilot-Streaming. The frameworks serves as basis for the Mini-App framework discussed in section 5. In section 6 we conduct an in-depth evaluation of the Pilot-Streaming framework. Further, we utilize the framework to conduct a characterization of various streaming workloads using synthetic mini applications.

#### 2 BACKGROUND AND RELATED WORK

We define a streaming application as an application that processes and acts on an unbounded stream of data close to real time. In this section we describe the current state of streaming middleware and infrastructure and related work. As alluded in Fox et al. [16], there is no consensus on software and hardware infrastructure for streaming applications, which increases the barrier for adoption of streaming technology in a broader set of application. Notwithstanding the lack of general consensus, in this paper we will explore the usage of the existing Pilot-Abstractions as a unified layer for the development of streaming applications.

# 2.1 Streaming Middleware and Infrastructure

The landscape of tools and frameworks for stream processing is heterogeneous (see [24] for survey). The majority of these tools are open source and emerged in the Hadoop ecosystem. In the following, we briefly highlight three main components for stream processing (see Figure 1): the message brokering system, the storage and the stream processing engine.

**Message Broker:** Message broker are an important component of streaming applications decoupling data producer and consumer providing a reliable and durable data buffer and transfer supporting high throughputs. For this purpose, the brokering system typically provides a publish-subscribe interface. The best throughputs are

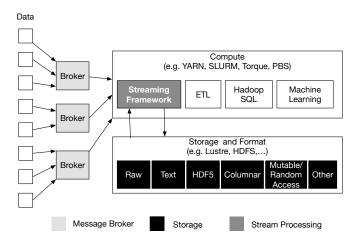


Figure 1: Streaming Applications Architecture: The message broker decouples streaming applications from incoming data feeds and enables multiple applications to process the data. The streaming framework typically provides a windowing abstraction on which user-defined functions can be performed.

achieved by log-based brokering systems, such as Kafka [53]. Facebook Logdevice [37] provides a similar log abstraction, but with a richer API (record not byte based) and improved availability guarantees. Apache Pulsar is another distributed brokering system [22]. Other types of publish-subscribe messaging system exist, such as ActiveMQ and RabbitMQ, but are generally less scalable than distributed log-based services, such as Kafka [26]. A message broker enables application to observe a consistent event stream of data at its own pace executing complex analytics on that data stream. Kafka is one such distributed message broker optimized for large volume log files containing event streams of data. Amazon Kinesis [2] and Google Cloud Pub-Sub [18] are two distinct message brokers offered as "platform as a service" in the cloud.

Data Processing Engines for Streaming: The increasing demands lead to a heterogeneous landscape of infrastructures and tools supporting streaming needs on different levels. Batch frameworks, such as Spark [54] and Dask [10], have been extended to provide streaming capabilities [38, 55], while different native streaming frameworks, such as Storm [52] and Flink [5] have emerged. Apache Beam [4] is stream processing engine available both as a library on top of Flink and Spark as well as a managed service in the Google cloud called Google's Dataflow [1]. Apache Beam's abstraction is based on a rigorous model for stream processing and provides welldefined and rich semantics for windowing, transformations and other operations. The different stream processing engines differs significantly in the ways they handle events and provide processing guarantees: Storm and Flink continuously process data as it arrives. Dask Streamz and Spark Streaming rely on micro-batches, i. e., incoming data is partitioned into batches according to a user-defined criteria (e.g. time window). The advantage of micro-batching is that it provides better fault tolerance and exactly-once processing

guarantees, while native stream engines can provide better latencies and more advanced windowing capabilities, e. g., tumbling and session-based windows.

Each of the described message brokers and stream processing frameworks provides unique capabilities, e. g., specific windows semantics, high-level APIs (such as streaming SQL), low latency. However, they do not address interoperability, deployment on HPC and resource management. While all frameworks provide an application-level scheduler, resource management is typically a second-order concern and not addressed in a generalized, holistic, frameworkagnostic approach.

#### 2.2 Related Work

There are several areas of related work: (i) frameworks that allow the interoperable use of streaming frameworks on HPC, (ii) the usage of HPC hardware features and frameworks (such as MPI) to optimize data streaming frameworks, and (iii) the exploration of data streaming in distributed applications.

Interoperable Streaming on HPC: Various tools have been proposed to support open source Big data frameworks, such as Hadoop and Spark on HPC environments on top of schedulers like SLURM, PBS/Torque etc [15, 27]. Other more streaming-oriented frameworks, such as Flink, Heron and Kafka are not supported on HPC out-of-the-box and require the manual implementation of job submission scripts.

While these script-based approaches is acceptable for small applications, it has severe limitations with respect to maintainability and support for more complex stream processing landscapes. For example, it is typically necessary to coordinate resources among several tools and frameworks, such as simulation and data acquisition, data message broker, and the actual stream processing framework. Also, streaming application are much more dynamic exhibiting varying data production and process rates, than traditional simulation and data analytics applications. Thus, in this paper we propose the usage of the Pilot-Abstraction as unifying layer for managing a diverse set of resources and stream processing frameworks.

Optimizing Streaming on HPC: The ability to leverage HPC hardware and software capabilities to optimize Big Data frameworks has been extensively explored. Kamburugamuve et al. [23] propose the usage of optimized HPC algorithms for low-latency communication (e.g. trees) and scheduling of tasks to enhance distributed stream processing in the Apache Storm framework [52]. In [25] they investigate the usage of HPC network technology, such as Infiniband and Omnipath, to optimize the interprocess communication system of Heron [28], the successor of Storm. Chaimov et al. [9] propose the usage of a file pooling layer and NVRAM to optimize Spark on top of Lustre filesystems. These approaches can complimentary to the high-level resource management approach proposed in this paper and can be used to optimize critical parts of a stream processing pipeline. These approaches mainly focus on lowlevel optimization of Big Data frameworks for HPC. Pilot-Streaming address critical gaps in the integration of these frameworks with the application and the ability to manage resources across these frameworks in a high-level and uniform way.

**Streaming in Scientific Application:** Fox et al. [24] identifies a broad set of scientific applications requiring streaming capabilities.

Many aspects of these use cases have been explored: For example, Bicer et al. [7] investigates different light source reconstruction techniques on HPC. Du [13] evaluates streaming infrastructure for connected vehicle applications. Both approaches focus solely on a specific aspect of a single use cases, e.g., latencies or processing throughput. Proving a generalized architecture and solution for many use cases addressing important shared concerns, such as resource management, is not in scope of these approaches. Pilot-Streaming and the Streaming Mini-Apps provide a holistic approach for addressing a broad set of use cases end-to-end from data source, broker to processing on heterogeneous infrastructure.

The implementation of scientific streaming applications requires the integration of infrastructure, a diverse set of frameworks: from resource management, message brokering, data processing to advanced analytics. In most cases, the data source is external making it essential for streaming application to dynamically manage resources and frameworks.

#### 3 STREAMING APPLICATIONS

Stream processing is becoming an increasingly important part of scientific applications. While traditionally streaming applications primarily performance simple analytics (smooth averages, max detection) on the incoming data stream, the computational demands are growing. For example, to run complex reconstruction algorithms for light source data streams or deep learning based computervision algorithms, such as convolutional neural networks, a vast amounts of scalable compute resources are required. In this section, we develop a taxonomy for classifying streaming applications. Further, we will discuss light source streaming as specific applications example.

## 3.1 Applications Characteristics

In the following we investigate different types of streaming applications. As illustrates in Figure 2 these types are used to characterize in particular the coupling between data generation (simulation, experiment) and analysis (e. g. streaming analytics):

- Type 1: **Experiment and Streaming Application:** Experimental data generated by an instrument that is processed by a data analysis application and/or a simulation. An example are light source experiments (see section 3.2).
- Type 2: **Simulation and Streaming Application:** Simulation produces data that is processed by a data analysis application. This form of processing is referred to as in-situ processing. Different forms of in-situ analysis exist: the analysis tasks can e.g. run within the same HPC job or on a separate set of nodes coupled via shared storage and/or network. An example of co-analysis of molecular dynamics simulations data [36].
- Type 3: Simulation/Experiment with Feedback: Simulation/Experimental data that is processed. Output is used to
  steer simulation respectively experiment in a feedback
  loop. Both type 1 and 2 applications typically benefit from
  the ability to integrate real-time insights into an experiment or simulation run.

Streaming applications involve the coupling a data source (simulation, experimental instrument), message broker and the actual

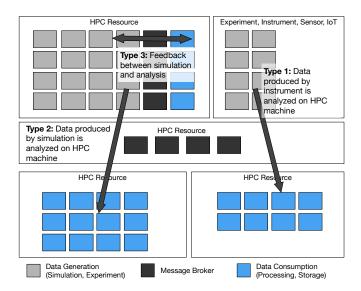


Figure 2: Streaming Application Types: Type 1: experiment is producing data that is fed into an analysis phase. Type 2: Simulation is producing data that is streamed into an analysis phase. Type 3: Same as Type 1 or 2 but including feedback into data source, which typically requires co-location.

stream processing. The resource needs for all three components, i. e. for data production, message brokering and processing is highly dependent on the application characteristics. Frequently, the resource requirements can change at runtime.

The coupling between data source and processing can be (i) direct (e. g., using a direct communication channel, such as memory) or (ii) indirect via a brokering system. The direct couple is used when low latencies and realtime guarantees are required. The direct coupling approach is however associated with several drawbacks: it typically involves a large amounts of custom code for interprocess communication, synchronization, windowing, managing data flows and different data production/consumptions rates (back-pressure) etc. Thus, it is in most cases advantageous to de-couple production and consumption using a message broker, such as Kafka. Another concern is the geographic distribution of data generation and processing: both can be co-located in the same data center or geographically distributed. Further, the number of producer and consumers can vary.

The third component is the actual stream data processing: in simply cases the application utilizes non-complex analytics on the incoming data, e. g. for averaging, scoring, classification or outlier detection. Typically, streaming applications utilize less complex analytics and operate on smaller amounts of data, a so-called streaming window. There are multiple types of windowing, e. g. a fixed, sliding or session window. Commonly the streaming windows is either defined based on processing time or event time. More complex application involve combine analytics with state and model updates, e. g. the update of a machine learning model using incoming and historical data. This processing type requires that the model state is retained. Further, access to additional data is often required.

The big data ogres [17] provide a conceptual model for characterization of data-intensive applications comprising of four views with different facets. The execution view characterizes issues like computational complexity, I/O, and memory; the problem architecture defines the overall structure of the application (e.g., the style of parallelism); the data source view focuses on aspects related to the data source. In the following, we use a subset of the views and facets defined by the big data ogre framework to characterize and describe streaming applications. The main difference to traditional, data-intensive batch applications is that streaming data sources are unbounded. While this impacts some aspects of an applications, such as the runtime and the potentially need to carefully reason about ordering and time constraints, other factors remain the same, e.g., the computational complexity of the processing algorithms. In the following, we utilize the following sub-set of properties to characterize streaming applications:

- Data Source and Transfer: describe the location of the data source in relation to the stream processing application. The data source can be external (e. g., an experimental instrument) or internal to the application (e. g., the coupling of a simulation and analysis application on the same resource). Output data is typically written to disk or transferred via a networking interface. Message brokers can serve as intermediate decoupling production and consumption.
- Latency is defined as the time between arrival of new data and its processing.
- Throughput describes the capacity of the streaming system, i. e. the rate at which the incoming data is processed.
- **Lifetime:** Streaming applications operate on potential unbounded data streams. The lifetime of a streaming application is often bound to the data source. In most cases it is not infinite and limited to e.g. the simulation or experiment runtime.
- Time/Order Constraints defines the importance of order while processing events.
- Dynamism: Defines to what extend does the data rates and processing complexity changes during the lifetime of a streaming application.
- **Processing:** The processing characteristics describes the complexity of data processing that occurs on the incoming data. Typically, the processing complexity depends on the amount of data being processed (window size, historic data) and the properties of the algorithms.

## 3.2 Application Examples

In the following we utilize the defined properties to characterize to example use cases: (i) a generic streaming analytics application (Type 1 or 2), and a more specific use case (ii) light sources analytics (Type 1). Table 1 summarizes different characteristics of these applications.

3.2.1 Streaming Analytics. Use cases, such as Internet-of-Things, Internet/Mobile clickstreams, urban sensor networks, co-analysis of simulation data, demand the timely processing of data feeds using different forms of analysis [11, 16]. For example, an increasing number of scientific applications require streaming capabilities: cosmology simulations require increasing amounts of data analytics to digest simulation data, environmental simulation require the

integration of remote sensing capabilities, etc. Depending on the nature of the data source, this type of application can be classified as type 1 or 2 application. The number of type 3 application is still comparable low. This can be attributed to the lack of sufficient middleware to support such complex architectures.

While the general problem architecture of data analytics and machine learning are similar to those of batch application, there are some subtle differences: typically the amount of data processed at a time is small compared to batch workloads. While the problem architecture of many machine learning algorithms remains the same, different techniques for updating the model using the new batch of data are used (e.g. averaging using a decay factor).

3.2.2 Light Source Sciences. X-Ray Free Electron Laser (XFEL) are a class of scientific instruments that have become instrumental for understanding fundamental processes in domains such as physics, chemistry and biology [14, 20]. Such light sources can reveal the structural properties of proteins, molecular and other compounds down to the atomic levels. The light source emits hundreds to thousands of x-ray pulses per second. Each pulse produces an image of the diffraction pattern as results. These images can then be combined and reconstructed into a 3-D model of the compound serving as the basis for a later analysis. Light sources can be used to exactly observe what is happening during chemical reactions and natural processes, such protein folding.

Example for XFEL light sources are the Linac Coherent Light Source (LCLS) [49] at SLAC, the National Synchroton Light Source II (NSLS II) [8] at Brookhaven, and the European XFEL light sources [44]. LCLS-I averages a throughput of 0.1-1 GB/sec with peaks at 5 GB/s utilizing 5 PB of storage and up to 50 TFlops processing [3]. The European XFEL produces 10-15 GB/sec per detector [44]. In the future even higher data rates can be expected: LCLS-II is estimated to produce data at a rate of more than 20 GB/sec. Advanced computing capabilities are required to process data streams from these detectors (e.g., using image processing) in near realtime as well as for steering the experiment.

Light source applications are typically a Type 1 application. In most cases the instrument is co-located with some compute resources. However, scientists often rely on additional compute resource and also may integrate data from several instruments. Thus, the ability to manage geographically distributed resources in an important. Currently, data analysis is often decoupled from the experiments. With the sophistication of the instruments, the demand for steering capabilities will increase. Thus, this application will evolve toward a Type 3 application.

The processing pipeline for light source data typically comprises of three stages: pre-processing, reconstruction and analysis [19]. Pre-processing can includes e. g. normalization of the data, filtering and the correction of errors. Various reconstruction with different properties, such as computational requirements and quality of the output, exist: GridRec [12] is based on a Fast-Fourier transformation and is less computational intensive and thus, fast. Iterative methods can provide a better fidelity. An example of an iterative method is Maximum likelihood expectation maximization (ML-EM) reconstruction [45]. A broad set of analytics methods can be

|             | Streaming Analytics: K-Means     | Light Source                      |
|-------------|----------------------------------|-----------------------------------|
| Data Source | external or internal             | external                          |
| Latency     | medium/high latencies acceptable | low latencies                     |
| Throughput  | medium                           | high                              |
| Duration    | data source runtime              | experiment runtime                |
| Time/Order  | not important                    | not important                     |
| Constraints |                                  |                                   |
| Dynamism    | varying data rate                | varying data rate                 |
| Processing  | Model score: Assign incom-       | Reconstruction: Reconstruc-       |
|             | ing data to centroids to find    | tion techniques with different    |
|             | class O(num_points ·             | complexities (GridRec, ML-EM).    |
|             | num_clusters). Model up-         | Analysis: data analysis models,   |
|             | date: Update centroids with      | image processing models utilizing |
|             | in-coming mini-batch of data.    | GPUs                              |
|             | Model size: small (O(number      |                                   |
|             | clusters))                       |                                   |

**Table 1: Streaming Application Properties** 

used for analyzing the reconstructed image, e.g. image segmentation techniques using traditional computer vision or deep learning methods.

3.2.3 Discussion. The requirements of streaming applications vary: For use cases involving physical instruments with potential steering requirement, e. g., X-Ray Free Electron Laser, both latency and throughput are important. Other use cases e. g. the coupling of simulation and analysis have less demanding latency and throughput requirements. The lifetime of scientific streaming applications is often coupled to the lifetime of the data source. Time and message ordering is in contrast to transactional enterprise applications not important for many scientific applications. With respect to the data transfer and processing requirements, the need to support different frameworks in a plug-able and interoperable way is apparent.

Another important difference is that streaming applications are typically runtime constrained, i. e. they must process the incoming data at a certain rate to keep the system balanced. Thus, a good understanding of application characteristics is even more critical for streaming applications. Minor changes in the data rates, the processing approach (e. g. change of the processing window, sampling approaches or the need to process additional historic data or available resources can lead to imbalance and a dysfunctional system. Thus, the ability the dynamically allocate additional resources to balance the system is critical. We use the characteristics identified in the section to design a Streaming Mini-App frameworks that aids the evaluation of complex streaming applications and infrastructure (see section 5).

# 4 PILOT-STREAMING ARCHITECTURE, ABSTRACTIONS AND CAPABILITIES

Pilot-Streaming addresses the identified challenges and gaps related to deploying and managing streaming frameworks and applications on HPC infrastructure. It provides a unified abstraction across frameworks, such as Kafka, Spark and Dask, and enables dynamic resource management, a critical requirement identified during the application characterization.

The framework was designed to meet the following three key requirements: (i) the ability to support stream processing and brokering frameworks on HPC in a plug-able and extensible way, (ii) high-level abstractions that provide sufficient flexibility to the application while supporting the resource management and performance needs of streaming applications are essential, and (iii) the need to

dynamically allocate resources to balance data production and processing.

To achieve these objectives, Pilot-Streaming is based on the Pilot-Job concept. A Pilot-Job is a system that generalizes the concept of a placeholder job to provide multi-level scheduling to allow application-level control over the system scheduler via a scheduling overlay [34]. Pilot-Jobs have been proven to provide efficient mechanisms for managing data and compute across different, possibly distributed resources. The Pilot-Abstraction is heavily used by many HPC application for efficiently implementing task-level parallelism, but also advanced execution modes, such as processing of DAG-based task graphs. The Pilot-Abstraction is heavily used, e.g. molecular dynamics simulations [6] and in high energy [51]. We have explored the applicability of the Pilot-Abstraction [29] to data-intensive applications on HPC and Hadoop environment [31-33, 35]. In the following we describe the architecture and capabilities of Pilot-Streaming that allows it to manage the deployment of different stream processing frameworks, in particular Spark, Flink, Dask and Kafka, as well as its ability to serve as unified access layer to run tasks across these in an interoperable way.

Pilot-Streaming is an extensions of the Pilot-Abstraction to facilitate various streaming use cases as previously depicted in Figures 2. As seen in these figures, these applications typically require a set of different frameworks that need to be deployed side-by-side on the same or even different distributed resources. Pilot-Streaming allows the on demand deployment of the Kafka message broker to decouple production and processing of data. Further, various stream processing frameworks will be supported. A key capability of the Pilot-Framework is the ability to dynamically scale these frameworks by adding resources. This is essential to deal with varying data rates and compute requirements. Further, framework continuously monitors the framework adding a level of fault tolerance, which is essential as stream applications typically run longer than batch jobs.

Pilot-Streaming provides a high-level API for provisioning Dask, Spark, Flink and Kafka clusters as well as for running compute on these frameworks. The key features of Pilot-Streaming are:

- Unified and Programmatic Resource Management: The Pilot-Abstraction provides a unified resource management abstraction to manage streaming frameworks for processing and message brokering on HPC environments. It allows the orchestration of compute and data across different frameworks.
- Streaming Data Sources: While our previous work focused on integration static datasets and compute units managed by Pilot-Jobs [35], Pilot-Streaming extends this ability to streaming data sources, such as Kafka topics.
- Interoperable Streaming Data Processing: For the processing of streaming data applications can utilize the Pilot-API for defining Compute-Units. Compute-Units can either rely on native HPC libraries and applications or can integrate with stream processing frameworks, such as Spark-Streaming. This enables applications to utilize the different capabilities of these frameworks in a unified way.
- Extensibility and Scalability: Pilot-Streaming is extensible and can easily extended to additional message brokers and streaming frameworks. It is architected to scale to large (potentially distributed) machines both at deploy and runtime.

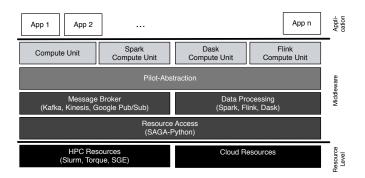


Figure 3: Pilot-Streaming Architecture: Pilot-Streaming allows the management of message brokers and diverse stream processing frameworks on HPC machines.

#### 4.1 Architecture

Figure 3 illustrates the high-level architecture of Pilot-Streaming. Pilot-Streaming provides a unified access to both HPC and cloud infrastructure. For resource access we utilize the SAGA Job API [42], a lightweight, standards-based abstraction to resource management systems, such as SLURM, SGE and PBS/Torque. The framework provides two key capabilities: the management of message broker on HPC and the management of distributed data processing Engines on HPC. These two capabilities are encapsulated in the message broker and data processing module. The interface to the framework is the Pilot-Abstraction [34], a proven API for supporting dynamic resource management on top of HPC machines. The application logic is expressed using so-called Compute-Unit, which can be executed in either (i) a task-parallel processing engine, such as Pilot-Jobs (e.g., RADICAL-Pilot [41], BigJob [30] or Dask), or (ii) a streaming framework, such as Spark Streaming or Flink. Case (i) typically requires the manual implementation of some capabilities, e.g. the continuous polling of data from a data source. In case (ii) the developer can rely on the streaming framework for implementing data windows or micro-batching. Both scenarios have trade-offs: while scenario (i) allows the interoperable execution of CUs across frameworks, scenario (ii) is often faster to implement. Pilot-Streaming supports both cases.

Figure 4 illustrates the control flow used by applications to manage Pilots in conjunction with the streaming frameworks and application-specific tasks, the so-called Compute-Units. In the first steps the application requests the setup of Spark, Dask or Kafka cluster using a Pilot-Description as specification. The framework than initiates a new Pilot-Job, a placeholder job for the data processing or message broker cluster, via the local resource manager. The component running on resource is referred to as Pilot-Streaming-Agent (PS-Agent). After the job and framework has been initialized, the application can start to submit compute units or initiative interactions with the native framework APIs via the context object. In addition, to managing streaming environments on HPC machines, Pilot-Streaming can integrate with cloud message brokers, such as Amazon Kinesis and Google Pub/Sub.

Pilot-Streaming is an extensible framework allowing the simple addition of new streaming data sources and processing frameworks. By encapsulating important components of streaming applications

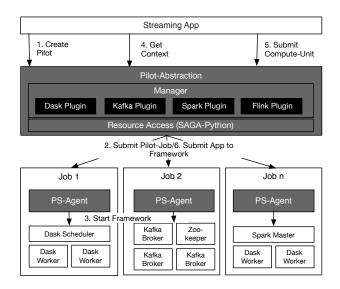


Figure 4: Pilot-Streaming Interaction Diagram: The figure shows the control flow used by Pilot-Streaming to manage frameworks and applications.

into a well-defined component and API, different underlying frameworks can be used supporting a wide variety of application characteristics. It utilizes the SAGA-Python [47] implementation to provision and manage resources on HPC machines. For this purpose, it accepts all attributes of the SAGA Job map 1-to-1 to the Pilot-Compute-Description, which is used to configure the framework's execution environment. All SAGA adaptors are supported. The streaming frameworks specifics are encapsulated in a plugin. A framework plugin comprises of a PluginManager implementation of a simple service provider interface (SPI) and a bootstrap script executed on the resource. As depicted in Listing 1, the interface comprises of six functions, e. g., to start/extend a cluster, to retrieve cluster information, such as state and connection details.

```
class ManagerPlugin():
    def __init__(self, pilot_compute_description)
    def submit_job(self)
    def wait(self)
        def extend(self)
    def get_context(self, configuration)
    def get_config_data(self)
```

Listing 1: Pilot-Streaming Plugin Interface

#### 4.2 Pilot-API Abstractions

In this section, we describe the provided abstraction from developer point of view. The framework exposes two interfaces: (i) a command-line interface and (ii) the Pilot-API for programmatic access. The API is based on a well-defined conceptual model for Pilot-Jobs: P\* [34]. The Pilot-API enables application developers to seamless integrate message brokers and other streaming data sources with computing resources. The abstraction allows reasoning about resources and performance trade-off associated with streaming applications. It provides the means necessary to tune and optimize application execution by adding/removing resources

at runtime. Listing 2 shows the initialization of a Pilot-managed Spark cluster. The user simply provides a pilot compute description object, which is a simple key/value based dictionary.

Listing 2: Pilot-Streaming: Creation of Spark Cluster

The same can also be achieved using the command line interface (see Listing 3).

#### **Listing 3: Pilot-Streaming: Commandline Interface**

A key capability of Pilot-Streaming is the ability to dynamically add/remove resources to the streaming cluster by just referencing a parent cluster in the Pilot-Description. Listing 4 shows an example how the API handles resource extensions. If the resources are not needed anymore, the pilot can be stopped and the cluster will automatically resize. This capability not only allows application to respond to varying resource needs, but also provides the ability to work around maximum job size limitations imposed by different resource providers.

Listing 4: Pilot-Streaming: Extension of Spark Cluster

Pilot-Streaming provides several hooks to integrate with the managed streaming frameworks. It supports custom configurations, which can be provided in their framework native form (e.g. sparkenv format etc.) and can easily be managed on per machine basis. This ensures e.g. that machine-specific aspects, e.g. amount of memory, the usage SSD and parallel filesystems, network configurations, can optimally be considered.

Pilot-Streaming supports interoperability on several levels. A Compute-Unit can be formulated and executed in a framework agnostic. Listing 5 illustrates how to execute a Python function in a interoperable way.

```
def compute(x): return x*x
compute_unit = pilot.submit(compute, 2)
compute_unit.wait()
```

## Listing 5: Pilot-Streaming: Interoperable Compute Unit

Further, the Context-API provides the ability to interface with the native Python APIs from these frameworks. The context object exposes the native client application, i. e., the Spark Context, Dask Client or Kafka Client object. Listing 6 shows an examples.

```
sc = spark_pilot1.get_context()
rdd = sc.parallelize([1,2,3])
rdd.map(lambda x: x*x).collect()
```

## Listing 6: Pilot-Streaming: Native Spark API Integration

This is in particular useful frameworks like Spark, Dask and Flink share many commonalities, like a MapReduce API and/or a task-based API. Using this capability functions can easily be ported between frameworks, e. g. to utilize advanced, framework-specific capabilities, such as specific window semantics or ordering guarantees. Of course, it is also possible to fully utilize all capabilities of each framework if interoperability is not required.

#### 4.3 Discussion

Data and streaming applications are more heterogeneous and complex than compute-centric HPC applications. Pilot-Streaming provides the ability to use different message broker and data processing engines in an interoperable way on HPC and cloud infrastructures. It removes the need for application developers to deal with low-level capabilities, such as resource management, cluster provisioning and monitoring. Running Spark, Kafka, Flink and Dask clusters across a flexible number of Pilot-Jobs provides the ability to dynamically adjust resources as needed during runtime. Further, the framework provides a common abstraction to execute compute tasks and integrate these with streaming data. It supports the interoperable execution of these CU across different frameworks. In addition, Pilot-Streaming provides the ability to also utilize the higher-level APIs provided by the frameworks. Currently, Pilot-Streaming supports Kafka, Spark, Dask, and Flink. It can easily be extended via a well-documented plugin-interface. Pilot-Streaming is open-source, maintained by an active developer community and available on Github [46].

#### 5 STREAMING MINI-APPS

There are various challenges associated with developing streaming applications: Developing streaming application pipelines is a complex task as it requires multiple parts: data source, broker and processing component. Every one of these components typically relies on different programming and middleware systems making it highly complex to develop such pipelines. During development process the real data source is often not available. Often developers have to rely on a static dataset, which results in significant efforts for setting setup a real test and development environment that is capable of mimicking non-bounded datasets as well as nonfunctional requirements, such as different data rates, message sizes, serialization formats and processing algorithms. If available, real applications are often not as parametrizable and tunable to characterize and optimize application, middleware and infrastructure configurations.

The Streaming Mini-App framework [50] addresses these challenges. Figure 5 shows the architecture of the Mini-App framework. The framework is based on Pilot-Streaming, which provides the ability to rapidly allocate different size of cluster environments. The core of the framework consists of two main components: (i) the MASS (Mini-App for Stream Source) can emulate a streaming data source, which can be tuned to produce streams with different characteristics: data rates, messages size. (ii) the MASA (Mini-App for

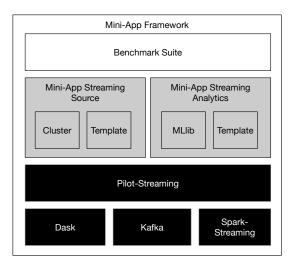


Figure 5: Streaming Mini-App Framework: The framework is based on Pilot-Streaming and provides two main components: the MASS (MiniApp for Stream Source) can emulate different kinds of streaming data sources and the MASA (MiniApp for Streaming Analysis) provides the ability to plug in synthetic processing workloads.

Streaming Analysis) provides a framework for evaluating different forms of stream data processing.

The MASS app includes a pluggable data production functions. The current framework provides two types of functions: A cluster source generates random data points following certain structures, e. g., for evaluation of streaming cluster analysis algorithms. The second type: template produces an unbounded stream based on a static template dataset. Data rates, message sizes etc. can be controlled via simple configuration options. Using these two base data source the majority of streaming applications can be emulated. For example, KMeans or other cluster algorithms for detecting outliers in data streams can be developed and tested with the cluster source. The template algorithms is great for migrating batch workloads to streaming. It can be used to emulate important application, such as light sources.

Similarly, the MASA app enables the user utilize machine learning algorithms from MLlib [39] or to provide custom data processing functions. Currently, it is based on Spark Streaming, but the framework can easily ported to other streaming frameworks as it is based on Pilot-Streaming. The processing function is data-parallel by nature. The machine learning algorithms provided by MLlib are capable of utilizing distributed resources supporting both data and model parallelism. In particular, we provide pre-configured support for KMeans clustering [48] and for reconstructing light source data. The K-Means algorithm has a complexity of O(cn) where c is the number of cluster centroids and n is the number of data points. The light source reconstructing algorithm is based on Tomopy [19], a framework that is commonly used for pre-processing raw light source data, e.g., image reconstructions, and for further analysis. Different reconstruction algorithms are supported by the Mini-App framework, e.g., GridRec [12] and ML-EM [45].

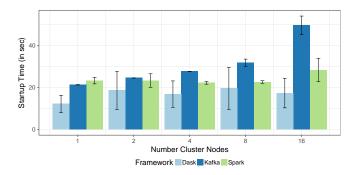


Figure 6: Kafka, Spark, and Dask Startup Time on Wrangler: Kafka start involves the startup of both Zookeeper and the Kafka brokers and thus, is most of the times longer than Spark. Dask has the shortest startup times. For all frameworks the startup time increases with the number of nodes.

In summary, the Streaming Mini-App frameworks provides optimal customizability with the ability to plug in custom data production and processing functions as well as various configuration parameters that control data rate, message sizes, etc. The framework provides comprehensive performance analysis options, e.g. it includes standard profiling probes that enables to measure common metrics, such as production and consumption rate allowing the benchmark of application and streaming middleware components making it easy to understand performance bottlenecks as well as the impact of changes. This is an essential capability to develop, test and tune streaming pipelines under complex, real world loads. In particular components like the message broker are difficult to analysis as the write/read load can vary significantly depending on the number consumers and producers. Further, the Mini-App frameworks allow for easy reproducibility of such experiments. The Streaming Mini-Apps provide a powerful tool to develop, optimize applications, and empirically evaluate streaming frameworks and infrastructure. In contrast to other approaches [40], the streaming mini app framework focuses on data-related characteristics, in particular the need to produce, transport and process data at different rates. In addition, the framework can emulate the application characteristics of K-Means application.

## **6 EXPERIMENT AND EVALUATION**

The aim of this section is to investigate different infrastructure configuration with respect to their ability to fulfill defined application requirements in terms of latency and throughput. In particular we propose the usage of a Mini-App framework that enables us to simulate different data production and data analysis characteristics. For the experiments, we utilize Wrangler, an XSEDE machine designed for data-intensive processing. Each Wrangler nodes has 128 GB of memory and 24 cores. Further, a local SSD can be used as intermediate storage. We investigate different configuration for data production, message broker and stream processing components. We utilize different synthetic and real-world workloads.

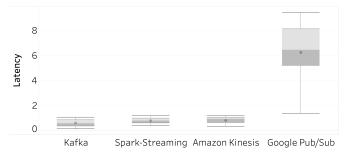


Figure 7: Latency: Kafka, Spark Streaming, Amazon Kinesis and Google Pub/Sub (100 messages/sec): Spark Streaming adds some latency in comparison to a simple Kafka consuming application.

## 6.1 Startup Overhead

There are two main steps for setting up Spark and Kafka on HPC: (i) Running the batch job that sets up the Kafka/Spark cluster and (ii) initiating an actual session with the broker respectively starting a Spark job by initializing a Spark session. Figure 6 compares the startup times for different size Kafka, Spark and Dask clusters. Pilot-Streaming supports the ad-hoc setup and scaling of cluster for stream computing. The measured startup times are short compared to the overall runtime of streaming application. in particular, considering the benefits of Pilot-Streaming: improved isolation of application components, the ability to independently scale parts of the streaming pipeline to the application needs, better diagnoseability, debug-ability and predictability of the application, this is an acceptable overhead.

#### 6.2 Latencies

Further, we investigate the latencies that users can expect from different configurations of stream processing pipeline. We evaluate the latency of the Kafka message broker and compare it to different cloud solutions. Further, we analyze the end-to-end latency between a data source, Kafka and the stream processing framework. For this experiment, we deploy Kafka and Spark each on a single Wrangler node. Further, we utilize a separate node for data production. In addition, we compare the latency to two cloud message brokers: Amazon Kinesis (deployed in us-east-1 region) and Google Pub/Sub service.

Figure 7 visualizes the latency measured between data production and data processing. With respect to latency the Kafka client has the lowest overhead. Spark Streaming adds minimal overhead to the processing latency. The amount of the overhead compared to a simple Kafka clients depends on the Spark Streaming micro-batch window size and varies between 3 sec (for the 8 sec batch window) and 0.2 sec (for the 0.2 sec microbatch window). Not surprisingly, the end-to-end latency measured for cloud services is significantly larger. In particular, Google's Pub/Sub services shows a higher latency of 6.2 sec in average.

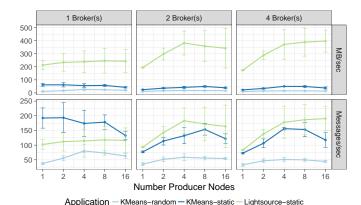


Figure 8: MASS Producer Throughput for Different Data Sources Types and Resource Configurations: We utilize up to 16 producer nodes/8 process per node and 4 Kafka broker nodes. The achievable throughput depends on the message size: for KMeans the message size is ~0.3 MB, for the light-source: ~2 MB.

## 6.3 Producer Throughput

In this section, we analyze the performance for publishing data into the Kafka system using the MASS app. The produces batches of random 3-D points, which are serialized to a string and pushed to Kafka using PyKafka [43]. We utilize different data source characteristics: (i) KMeans: every message consists of 5,000 randomly generated double precision points. The average serialized size of message is 0.32 MB; (ii) Lightsource: every message consists of raw input dataset in the APS data format and an average encoded message size of 2 MB.

The achievable Kafka write throughput depends on various factors in the different application and infrastructure components: data source, network and Kafka broker cluster. To understand the impact of different parameters, such as the number of Kafka partitions (in relation to the size of the Kafka cluster and the data source parallelism), message size, the data source parallelism per node in relation to the available network bandwidth, etc. In the following, we use Pilot-Streaming and the Mini-Apps to characterize important scaling properties of Kafka.

We investigate the throughput and its relationship to different MASS types and configurations as well as to different Kafka broker cluster sizes. For the experiment, we utilize different resource configuration parameters determined in a set of micro-experiments: the number partitions is fixed at 12 per node. On every producer node, we run 8 producer processes in Dask. While each nodes possesses 24 cores, the performance per node deteriorated drastically when using more producers/node due to network and I/O bottlenecks. We evaluate three scenario, KMeans-random, KMeans-static and Lightsource. The KMeans-random scenario uses the cluster MASS plugin to generate points randomly distributed around a defined number of centroids. Kmeans-static produces a static message at a configured rate. For both KMeans scenario, we use a message size of 5,000 points per message, which corresponds to a message

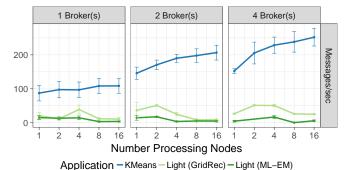


Figure 9: MASA Throughput for KMeans and two Light Source Reconstruction Algorithms: KMeans scales well with increasing numbers of processing and broker nodes. GridRec shows a higher throughput than ML-EM as it less computation complex. Scaling of both reconstruction algorithms is limited by I/O contention.

size of  $0.3\,\mathrm{MB}$ . The light source app produces a static message in the APS format, which has a serialized size of  $2\,\mathrm{MB}$ .

Figure 8 shows the results. The KMeans-random configuration is bottlenecked by the random number generator. Thus, the KMeans-static setup has on average 1.6x higher throughput than KMeans-random. The light source MASS performs in almost all scenarios best except for 1 broker. In all cases the performance drops significantly in particular for a small number consumers. However, for large numbers of messages and larger message sizes a broker cluster is essential. The 1 broker scenario shows a limited throughput for both the KMeans-static and Lightsource. This is probably caused by contentions due to the need to handle many concurrent broker connections and bottlenecks in network and I/O.

## 6.4 Processing Throughput

We use the MASA Mini-App to investigate the throughput of three different processing algorithms: a streaming KMeans application that trains a model with 10 centroids and makes a prediction on the incoming data, and two light source reconstruction algorithms: GridRec and ML-EM. We use the distributed KMeans implementation of MLlib and the GridRec, ML-EM of TomoPy. In the experiment we utilize the MASS Mini-App with 1 node/8 producer processes to continuously produce messages of 0.3 MB/5000 points for KMeans and 2 MB/1 point for the light source scenarios. This way are able to simulate a complex read/write workloads on the Kafka broker. We use 12 partitions/node for the Kafka topic. The Mini-App relies on Spark Streaming and a mini-batch window of 60 sec for executing the different streaming workloads.

Figure 9 shows the results of the experiment. The processing throughput depends on various aspects, such as the bandwidth to the message broker, computational complexity, and the scalability of the processing algorithm. The KMeans application shows the highest throughput. It scales both increasing number of processing nodes. For example, it is apparent that in the 1 and 2 broker scenario, the I/O to the broker constraints the performance. With additional broker nodes, the available bandwidth and parallelism increasing. Spark Streaming assigns 1 task per Kafka partition. This

is visible in a significant increase in throughput. With KMeans we were able to achieve a maximum throughput of 277 messages/sec and thus, were easily able to sustain the generated data rate.

The throughput of the light source reconstruction algorithms is significantly worse with maximum 63 message/sec for GridRec and 22 messages/sec for ML-EM. As describe iterate algorithms, such as ML-EM are more demanding than GridRec. Additional broker nodes yielded in significant performance improvements. Additional processing nodes improved the performance as long the bandwidth to the resource broker was able to keep up with the additional processing resources. The amount of data transferred is with 2 MB/message significant larger than in the KMeans scenario. Further, we observed some resource contentions caused by running multiple instances of the algorithm on the same node and the need to buffer a significant number of messages. The results show the importance of resource management - only if the bandwidth and read-parallelism to the data source or broker is large enough additional compute resources are beneficial.

## 6.5 Discussion

As demonstrated, the overhead for Pilot-Streaming is acceptable: the startup time for dynamically starting Kafka, Dask and Spark clusters although small, is outweighed by the benefits of improved flexibility, resource isolation (per application components), and the ability to scale components independently (at runtime if needed). We demonstrated the scalability of the framework by managing large streaming landscapes of Dask, Spark and Kafka concurrently on up to 32 nodes, 1536 virtual cores, and 4 TB of memory achieving throughputs of up to 390 MB/sec for the lightsource scenario. This throughput is large enough to sustain the LCLS-I data stream with a high enough sampling rate. At the current setup, the processing side is the bottleneck. We are only able to process a fraction of the throughput. Scaling stream processing is more difficult than scaling batch analytics workload as it requires a careful balance of bandwidth to/from the data source respectively the broker and compute resources. In particular, it can be difficult to diagnose bottlenecks in the broker, as the varying mixture of write/read I/O makes the performance often unpredictable. Pilot-Streaming provides the necessary abstractions to manage resources effectively at runtime on application-level.

The Streaming Mini-App framework simplifies streaming application development and performance optimizations. Using the Streaming Mini-App framework, we were able to emulate various complex application characteristics. It is apparent that the different frameworks and application components each have unique scaling characteristics and resource needs. Even for optimization of just one component a large number of combinations of experiments is required. On streaming application-level this leads to a combinatorial explosion of configurations. The Streaming Mini-Apps and Pilot-Streaming provide essential tools for automating this process. In the future, we will use both frameworks as foundation for higher-level performance optimization approaches, e. g., modeling the performance of each component, the usage of experimental design and machine learning techniques for performance predictions.

#### 7 CONCLUSION AND FUTURE WORK

Pilot-Streaming fills an important gap in supporting stream processing on HPC infrastructure by providing the ability to on-demand deploy and manage streaming frameworks and applications. This capability is crucial for an increasing number of scientific applications, e.g., light source science, that require stream processing at data rates of 20 GB/sec to generate timely insights and allow steering. The landscape of tool and frameworks for message brokering, data storage, processing and analytics is diverse. Pilot-Streaming currently integrates with Kafka, Spark Streaming, Dask and Flink. Its flexible, plug-in architecture allows the simple addition of new frameworks. Streaming applications can have unpredictable and often, external induced resource needs, e. g. driven by the data production rate. Pilot-Streaming addresses these needs with a well-defined resource model and abstraction that allows the adjustments of the allocated resources for each component at runtime. Another important contribution is the Streaming Mini-App framework, which simplifies the development of streaming pipelines with the ability to emulate data sources and different processing techniques. We demonstrated the variety of features of this framework with several experiments using a streaming KMeans as well as two different light source reconstruction algorithms.

This work represents the starting point for different areas of research: We will extend Pilot-Streaming to support highly distributed scenarios enabling applications to push compute closer to the edge exploiting improved data locality. The Streaming Mini-App framework will be the basis for the development and characterization of new streaming algorithms, e. g. additional reconstruction algorithms and deep learning based object classification algorithms. We will further explore the usage of accelerators (such as GPUs) to support compute-intensive deep learning workloads in this context. Another area of research are steering capabilities. Further, we will continue to utilize the Streaming Mini-Apps to improve our understanding of streaming systems and embed this into performance models that can inform resource and application schedulers about expected resource needs.

**Acknowledgements:** We thank Stuart Campbell (BNL) for guidance on the light source application. This work is funded by NSF 1443054 and 1440677. Computational resources were provided by NSF XRAC award TG-MCB090174.

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