Abstract
Serverless applications are usually composed of multiple short-lived, single-purpose functions exchanging data in reaction to events or changes of states. Existing function orchestration services coordinate functions and trigger their activation following some predefined rules (e.g., function dependency and state machine), while being oblivious to the underlying data exchange between functions. Such design has limited expressiveness and incurs high orchestration overhead: developers often need to manage complex function interactions by themselves, and the performance can still be unsatisfactory.

In this paper, we advocate data-centric orchestration where function invocations are triggered by the flow of data. In our design, the platform provides data trigger APIs through which developers can control when and how the output of one or many functions is passed to other functions as input and triggers their executions. With explicit support of data triggers, complex function interactions can be easily implemented, and data locality can also be satisfied. As a manifestation of this design, we present Pheromone, a scalable, low-latency serverless platform. Pheromone schedules functions close to the input with a two-level, shared-nothing scheduling hierarchy. Compared to existing commercial and open-source platforms, Pheromone cuts the latencies of function interactions and data exchanges by orders of magnitude, and scales well to complex workflows with long function chains and high parallelism. Case studies further demonstrate that Pheromone enables easy implementations of many applications, including real-time query, stream processing, and MapReduce sort.

1 Introduction
Serverless computing (aka Function-as-a-Service or FaaS) is gaining increasing popularity in the cloud. It allows developers to write highly scalable, event-driven applications as a set of short-running, stateless functions. Developers simply specify the events that trigger the activation of those functions, and let the platform handle resource provisioning, autoscaling, logging, and fault-tolerance. Serverless computing is also economically appealing as it promises zero cost of idling: developers are charged only when their functions are running.

The lowered management burdens and the fine-grained usage-based pricing have driven a host of applications to migrate to the serverless cloud [25,32,43,47,57,71,75]. These applications typically consist of multiple interactive functions with diverse invocation and data exchange patterns. For example, a serverless-based batch analytics job may trigger hundreds of parallel functions for all-to-all data exchange in the shuffling phase [48, 57, 77]; a stream processing application repeatedly triggers one or more functions to process dynamic data received in a time window; a microservice-based application runs short-lived functions with a high invocation rate that demands sub-millisecond invocation overhead [46].

In support of diverse function invocation and data exchange patterns, the serverless platform should ideally provide an expressive, easy-to-use function orchestration service that allows developers to compose complex workflows beyond simple compositions (e.g., chaining and branching). The orchestration should also be efficient, enabling low-latency invocation and fast data exchange between functions.

However, current serverless platforms fall short in meeting these requirements. They model a serverless application as a workflow that connects functions following their invocation dependency [3,10,18,21,31,50,51,64]. Such design only specifies how functions in a workflow are invoked, but is oblivious to how data are exchanged between those functions. Without such knowledge, the orchestrator can only assume that the output of a function is entirely and immediately consumed by the next function(s) in the workflow. This assumption does not hold true in many applications, such as the ‘shuffle’ operation in batch analytics and the processing of accumulated data batches in stream analytics (detail in §2.2). Developers are hence forced to manually manage function interactions and data exchanges, by choosing from a myriad of implementation approaches such as a message broker or a shared storage [5, 9, 21, 28, 48, 64], either synchronously or asynchronously. As there is no single best approach that always outperforms the others (detail in §2.2), developers may need
to write complex logic to dynamically select the most efficient approach in runtime. In addition to the limited expressiveness and usability, current serverless platforms are ill-fitted for latency-sensitive and data-intensive applications: they incur function interaction latency of tens of milliseconds, and such overhead is substantially increased under many chained functions and large data exchanges.

In this paper, we argue that function orchestration should follow the flow of data rather than the high-level function invocation dependency, which we call a data-centric approach. Our key insight is to make data consumption explicit and let it trigger functions and drive the workflow. In our design, the platform provides a rich set of data trigger APIs through which developers can flexibly specify when and how the intermediate data are consumed such that the intended downstream functions can get triggered accordingly. With a fine-grained control of data consumption, developers can freely express sophisticated function invocations and data exchanges in a workflow, using a unified programming interface. From the platform’s perspective, knowing how exactly the intermediate data will be consumed enables better scheduling of downstream functions to retain data locality, making it possible to achieve a low function interaction latency.

As an engineering practice of the data-centric approach, we present Pheromone, an efficient serverless platform that promises expressiveness, ease of use, and low-latency function orchestration at scale. Pheromone adopts three key designs to deliver high performance. First, it employs a two-level, distributed scheduling hierarchy to maximize the chances of local invocations. In Pheromone, each worker node runs a local scheduler that keeps track of the execution status of a workflow and locally invokes downstream functions by scheduling them onto the idle executors. In case that all executors are busy, the scheduler forwards the request to a global coordinator, which then routes the request to another worker node with available resources. Second, Pheromone trades the durability of intermediate data, which are usually short-lived and immutable, for fast data sharing. It applies various system-level optimizations such as zero-copy over shared memory for data sharing between local functions and direct data transfer between remote functions. Third, Pheromone employs sharded coordinators, each handling a disjoint set of workflows. Under such a shared-nothing architecture, local schedulers only synchronize the workflows’ execution statuses with the corresponding coordinators, which themselves require no synchronization, thus ensuring high scalability to distributed scheduling.

We evaluate Pheromone against the commercial and open-source serverless platforms with state-of-the-art performance, including AWS Lambda (with Step Functions), Azure Durable Functions, Cloudburst [64], and KNIX [21]. Evaluation results show that Pheromone improves function invocation latency by up to $140 \times$ and $1657 \times$, compared with highly-optimized open-source platforms and commercial platforms, respectively. Pheromone scales well to large workflows and only incurs millisecond-scale overhead even under 1k chained functions and 4k parallel functions, which outperforms existing serverless platforms by over 400$x$. Pheromone also leads to negligible overhead in data exchanges (e.g., 10s µs), thanks to its zero-copy data sharing. Case studies of various applications, including real-time query, stream processing, and MapReduce sort, further demonstrate that Pheromone can easily express the interaction patterns of complex workflows (rich expressiveness), simplify the application deployment with no need to handle data exchange (high usability), and efficiently execute latency-sensitive and data-intensive applications (wide applicability).

2 Background and Motivation

2.1 Serverless Computing

Serverless computing, with one of its popular incarnations being Function-as-a-Service or FaaS, has become a prevalent cloud computing paradigm [7, 15, 19]. Developers package their application code as a set of functions, specify the interactions among functions as sophisticated workflows, and then deploy them onto a serverless platform; whereas, the serverless platform operator takes the full responsibility of elastically managing resources for these functions and orchestrating their executions to meet their individual varying demands. As such, developers focus only on the application logic without managing server resources, thus serverless computing. Such concepts of high elasticity and operational simplicity have gained a lot of traction, and an increasingly large number of developers have migrated their applications onto serverless platforms [25, 32, 37, 43, 47, 57, 71, 75].

2.2 Limitations of Current Platforms

Current serverless platforms typically take a function-oriented approach to orchestrate and execute the functions of a serverless application. Specifically, this approach treats each function as a single and standalone unit, and separately expresses the interactions among functions as a workflow. The workflow connects individual functions following their invocation relationships, where each function can be triggered by the output of its preceding function(s). For example, many serverless platforms model an application as a directed acyclic graph (DAG) [3, 10, 18, 21, 31, 50, 51, 64], where the nodes represent functions and the edges indicate invocation relationships among functions. The DAG can be specified via general programming languages (e.g., Python) [3, 18] or domain-specific languages (e.g., Amazon States Language) [10, 21].

While the current function-oriented practice of serverless function orchestration is sufficient for some simple application patterns (e.g., a function chain in Fig. 1), it poses significant challenges to support more sophisticated and demanding
Limited expressiveness. Running modern applications on serverless platforms requires the knowledge of not only how functions in a workflow are invoked, but also how these functions exchange data. Take the ‘shuffle’ operation in a classic analytics job as an example. This shuffle operation needs a fine-grained, all-to-all data exchange between the functions of two stages, as shown in Fig. 1(right). Based on the output keys, each first-stage function’s output values are shuffled and redistributed to different second-stage functions. In addition, only after the first stage completes, the workflow can invoke the second-stage functions in parallel. With current serverless platforms, developers need to manually implement such data exchange via an external storage [48, 57], which is neither flexible nor efficient.

Take the batched stream analytics as another example where a function needs to process the data continuously received during a time window [38, 70], as shown in Fig. 1 (bottom left). A serverless workflow fails to express this pattern as the function is not immediately invoked upon data arrival. Developers typically depend on other cloud services (e.g., AWS Kinesis [6]) to batch the data for function invocations [25–27]. Note that, even with the latest stateful workflow [14], an addressable function needs to keep running to receive data, and such a function unnecessarily occupies compute resources and still leads to unsatisfactory performance (see §6.4).

In a nutshell, current serverless platforms assume that data flows in the same way as how functions are invoked in a workflow, and a function passes its result to others by directly invoking them. However, this often does not hold true as aforementioned. Current platforms have little support for developers to specify the patterns of data shared among functions, which significantly limits the expressiveness of a workflow and mandates developers to explore their own workarounds.

Limited usability. Current serverless platforms provide a large number of options for function interactions and data exchange. Functions can exchange data via a message broker or a shared storage [5, 9, 21, 28, 48, 64], either synchronously or asynchronously. In addition, they can process data from various sources like nested function calls, message queues, or other cloud services [20].

However, the presence of these many options significantly complicates the serverless application development and deployment, and in turn impacts the usability of serverless platforms. This is because there is no best approach that always outperforms others, forcing developers themselves to find the way to efficiently exchange data among functions. For example, we compare four approaches to passing data between two AWS Lambda functions: calling a function directly (Lambda), letting AWS Step Functions execute the two-function workflow (ASF)\(^1\), allowing functions to access Redis for fast data exchange (ASF+Redis), and configuring AWS S3 to invoke a function upon the data creation (S3) [29]. Fig. 2 shows their latencies under various sizes of data. It is clear that, no approach can consistently outperform others: 1) Lambda is efficient to transmit small data, 2) ASF+Redis is efficient to transmit large data, and 3) the data volume supported by different approaches is quite different, and only the S3 approach (though slow) can support virtually unlimited data exchange. This result imposes significant burden on developers to profile the data patterns of their applications and optimize the performance of data exchanges among interacting functions.

What makes this situation even more difficult, if not impossible, is that the data volume exchanged among functions can largely depend on the workloads, which may be irregular or unpredictable; therefore, there may be no best fixed approach for a set of interacting functions, and developers may have to write complex logic to select the best approach during service time. In addition to performance tuning, developers also need to consider the interaction cost. Previous work has highlighted the tricky trade-off between I/O performance and cost when using different storage to share intermediate data [48, 57], which further exacerbates the usability issue. Altogether, these current practices brings a truly non-serverless experience to developers as they still have to deal with server and platform characteristics.

Limited applicability. Current serverless applications target scenarios where there is a varying workload of requests and each request can invoke a workflow consisting of multiple

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\(^1\)We use the Express Workflows in our experiments as it delivers higher performance than the Standard Workflows [12].
As discussed in §2.2, the function orchestration in current serverless platforms usually have a function interaction delay of tens of milliseconds (see §6.2), and such delays get accumulated along with the length growth of a workflow of multiple functions. For example, in a workflow of 6 functions in AWS Step Functions, each function interaction causes a delay of more than 20ms and then the total platform-incurred delay is over 100ms, which may not be tolerable in many latency-sensitive applications [46]. In addition, without efficient support for sharing various-sized data among functions (as described earlier in ‘limited usability’), current serverless platforms are also an ill-fit for data-intensive applications [7, 21, 43, 46, 57, 64]. Altogether, these characteristics significantly limit the applicability of current serverless platforms despite their superior elasticity of resource management.

3 Data-Centric Function Orchestration

In this section, we propose the key technical building block (i.e., data-centric function orchestration) towards addressing the aforementioned three limitations in current serverless platforms. Later, we will elaborate upon how we leverage this technique to design a new serverless platform in §4.

3.1 Key Insight

As discussed in §2.2, the function orchestration in current serverless platforms allows a set of applications which consist of workflows with only simple data patterns and do not handle latency-sensitive and data-intensive scenarios efficiently. To partially mitigate these issues, developers have to put substantial manual efforts to redesign and reprogram their applications for deployments on current serverless platforms. This common practice is indeed non-serverless — developers have to carefully think about data patterns which is non-trivial because such patterns can be varying and unpredictable during service time, and they also have to dynamically select, if possible, proper data APIs from a big mix given by the platform for better performance.

One root cause of these issues is that today’s serverless function orchestration specifies only the coarse-grained dependencies among functions of the same workflow, but has little fine-grained control over how data exchange among these functions. It assumes that data flows in the same way as how functions are invoked in a workflow, and a function passes its result to others by direct function invocation. In particular, when a function returns its result, the workflow has no specific knowledge of how the result should be consumed (e.g., in full or chunks, directly or conditionally, immediately or delayed, etc.). Therefore, it has no choice but to send the entire result directly and immediately to the next function(s), following the invocation dependency. Though some platforms provide a few primitives that may allow developers to specify how to consume data (e.g., the Map state in AWS Step Functions [11]), they are not quite expressive and cannot express many data patterns in real-world applications, such as ‘shuffle’ as described in §2.2.

Our key insight is that, a desired serverless platform must allow fine-grained data exchange among functions of a workflow, while providing a unified and efficient approach for both function invocations and data exchange.

To materialize this insight, we propose a new data-centric approach to function orchestration which follows the data rather than the functions. We observe that intermediate data (e.g., results generated by functions) are typically short-lived and immutable [48, 65]: once they are generated, they wait to be consumed by downstream functions and then become obsolete.2 We therefore make data consumption explicit and let the data trigger (or invoke) functions. In particular, developers can simply specify how the intermediate data should be consumed such that downstream functions get triggered once the data that they need are ready, which can be applied to drive the execution of an entire workflow. Note that, using intermediate data to trigger functions leads to no consistency issues as such data are immutable and there are no updates once they are generated [48, 65].

The data-centric function orchestration has a great potential to effectively address the limitations of the current function-oriented orchestration. First, this data-centric orchestration breaks the tight coupling between function flows and data flows, and data do not have to follow the exact order of function invocation. It enables flexible and fine-grained data consumption, and therefore can express a rich set of serverless workflow patterns; thus, rich expressiveness. Second, this orchestration provides a simple, unified programming interface for both function invocations and data exchange, liberating developers from implementing complex logic via a big mix of APIs to optimize data exchange for function interactions; thus, high usability. Finally, with the fine-grained knowledge of data consuming, this brings huge optimization opportunities to improve locality in function invocations and data exchange, which can further enable even latency-sensitive and data-intensive workflows; thus, wide applicability.

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2 For data that need durability, they can be stored in a persistent storage which is not the focus of this paper.
3.2 Orchestration Primitives

Fig. 3 gives an overview of triggering functions in data-centric function orchestration. When deploying an application in Pheromone, it creates one or more data buckets that track intermediate data and serve as function triggers. Developers can configure the buckets with triggers that specify how and when data should invoke target functions. During a workflow execution, source functions directly send their results to the associated buckets. When a bucket detects any change to its data, it checks each associated trigger to determine whether the data required for that trigger are complete and ready to consume. If so, it automatically triggers target functions and transmits the associated data to them. This process takes place across all buckets, which collectively drive the entire execution of a workflow.

We design a variety of trigger primitives for buckets to specify how functions get triggered. Specifically, we identify that the interaction patterns among functions can be generally classified into three categories. Accordingly, we design our trigger primitives following these categories.

Direct primitive: This category allows functions to directly consume associated bucket data with no condition to be met.
- Immediate: It immediately triggers the functions once any object arrives. It can easily support sequential execution and invoke multiple functions in parallel (fan-out).

Conditional primitives: This category allows buckets to trigger functions only when specified conditions are met.
- ByBatchSize: It triggers functions when the number of accumulated data objects reaches a pre-specified threshold. For example, it can be used to easily enable batched stream processing [26, 27] similar to Spark Streaming.
- ByTime: It periodically triggers functions using data objects accumulated in a time window. It can be used to design the classic routine tasks [38, 70].
- ByName: It triggers functions only when the name of a data object matches a pre-defined value. It enables conditional function invocations by choice.
- BySet: It triggers functions only when all required objects specified in a set are complete and ready. It can be easily used to enable the assembling invocation (fan-in).
- Redundant: It triggers functions once \( k \) out of \( n \) objects associated with a bucket are ready. It supports executing redundant requests and performing the late binding, which can be commonly applied to improve performance and reliability [49, 58, 66].

As an example, we take the serverless-based ML model serving to illustrate our Redundant primitive, as shown in Fig. 4 (left). Serverless computing is well-suited for hosting scalable ML inferencing services [63, 71, 75]. An ML inferencing-serving pipeline typically needs to meet tight end-to-end tail latency constraints [39, 49, 75]. A common approach to reducing the tail latency is to leverage redundancy [49], in that we can have multiple executions (\( n > 1 \)) and wait only for the fastest one to complete (\( k = 1 \)). This primitive mitigates the straggler effects and optimizes the tail latency. In addition, when setting \( k \) to be more than 1, we can easily achieve reliable execution.

Dynamic primitive: The previous two categories focus on static primitives with no or pre-defined parameters, while this category allows the dynamic configuration of data patterns at service time.
- DynamicGroup: It allows a bucket to divide its associated data objects into multiple groups, each of which can be consumed by a set of functions. Here, the data grouping is dynamically performed based on the object metadata (e.g., by name). Once a group of data objects are ready, they trigger the associated set of functions.

We take the classic MapReduce to illustrate this primitive. The elasticity of serverless computing makes it a good fit to host interactive analytical jobs [47, 54, 57]. While MapReduce serves as a fundamental programming model in today’s data analytics systems [40, 74], it is challenging to directly perform MapReduce-style computations on current serverless platforms. As discussed in §2.2, it requires developers to trigger parallel functions at every stage and optimize the fine-grained, all-to-all data exchange between them [47, 48, 57].

We can easily address this issue via data-centric orchestration. Fig. 4 (right) shows how to use the DynamicGroup primitive to support MapReduce operations. When a function sends intermediate data objects to the associated bucket, it also specifies which data groups each data object belongs to. Once the ‘map’ functions complete, the bucket automatically triggers the ‘reduce’ functions, each consuming a group of objects.

Note that, our data-centric function orchestration provides a general paradigm for new serverless platform designs, and is not limited to the above primitives. In fact, we make the primitive implementation extensible with a common abstraction, allowing the future exploration of more primitives.

3.3 Programming Interfaces

Currently, we accept functions written in C++ and allow developers to specify function interactions with a Python client.

Function interface. To follow current common practice, Fig. 5 shows the handle() interface for developers to implement their functions. It is similar to the C++ main function,
### Table 1: The APIs of user library which developers use to operate on intermediate data objects and drive the workflow execution.

<table>
<thead>
<tr>
<th>Class</th>
<th>API</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EpheObject</td>
<td><code>void* get_value()</code></td>
<td>Get a pointer to the value of an object.</td>
</tr>
<tr>
<td></td>
<td><code>void set_value(val, size)</code></td>
<td>Set the value of an object.</td>
</tr>
<tr>
<td>UserLibrary</td>
<td><code>EpheObject* create_object(bucket, key)</code></td>
<td>Create an object by specifying its bucket and key name.</td>
</tr>
<tr>
<td></td>
<td><code>EpheObject* create_object(function)</code></td>
<td>Create an object by specifying its target function.</td>
</tr>
<tr>
<td></td>
<td><code>void send_object(object, output=false)</code></td>
<td>Send an object to its bucket, and set output flag if it needs to persist.</td>
</tr>
<tr>
<td></td>
<td><code>EpheObject* get_object(bucket, key)</code></td>
<td>Get an object by specifying its bucket and key name.</td>
</tr>
</tbody>
</table>

```c
int handle(UserLibraryInterface* library, \n    char* arg_values);
```

**Figure 5:** Function interface.

**Figure 6:** Configuring triggers for a Fibonacci workflow.

except that it takes the user library as the first argument. As shown in Table 1, the user library provides a set of APIs that allow developers to operate on intermediate data objects. These APIs enable developers to create intermediate data objects (i.e., EpheObject), set their values, and send them to buckets. When a bucket receives objects and decides to trigger the next functions, it automatically packages the relevant objects as the function augments (see Fig. 5). The function can also access other objects via get_object() if needed. In addition, send_object() allows developers to specify whether the object should persist after the workflow completes.

**Defining function interactions via bucket triggers.** We provide developers with a client to define how data should trigger functions in a workflow. In particular, this client creates buckets and configures triggers on these buckets using the primitives described in §3.2. Functions can then interact with the buckets by creating, sending and getting objects as described in Table 1.

Fig. 6 gives a simple example of configuring bucket triggers for a recursive Fibonacci workflow. In particular, developers create a bucket by the names (line 3), and then add triggers by specifying the BySet primitive and the metadata, i.e., the target function add and the key set (line 7). Once the \(i\)th Fibonacci number arrives, the add function gets triggered to sum up the \((i-1)\)th and \(i\)th numbers, and then writes the result back to the bucket as the \((i+1)\)th number. This process continues until the completion of all the triggers.

Altogether, with our orchestration primitives and intuitive programming interfaces, developers can conveniently implement their workflows to express various types of data patterns and function invocations (i.e., rich expressiveness), without choosing in ad-hoc from a big mix of APIs stemmed from different underlying systems like message broker, in-memory database, or persistent storage (i.e., high usability).

### 4 Pheromone System Design

In this section, we describe how we utilize the data-centric function orchestration to design a serverless platform with high-performance function interactions and data exchange.

**4.1 Architecture Overview**

Fig. 7 provides an overview of the Pheromone architecture, including four types of components: global coordinators, local schedulers, function executors, and shared-memory based object store. Specifically, user requests first arrive at the (global) coordinators, which route them to the (local) schedulers on worker nodes. The schedulers perform local scheduling, and send invocation requests to function executors that host user-provided function code. All schedulers and executors are run in individual containers atop the worker nodes. The shared memory on each worker node serves as the object store for intermediate data, which can efficiently exchange data objects within this node and with other nodes, as well as synchronize data that need to persist with durable key-value store.

Our data-centric orchestration (§3) already brings in two desired system properties, i.e., rich expressiveness and high us-
ability. The Pheromone design here focuses on how to further achieve high performance for wide applicability. It follows two principles: 1) minimizing the latencies of function invocations and data exchange, and 2) ensuring high scalability.

4.2 Distributed Scheduling

Pheromone employs distributed scheduling with global coordinators and local schedulers. This enables Pheromone to invoke functions as locally as possible, thus reducing the invocation latency. We present this design in a bottom-up manner.

Intra-node local scheduling. Pheromone's local scheduler uses the bucket triggers of a workflow to locally orchestrate its functions. Once a user request arrives, the scheduler starts the first function(s) of the workflow and tracks the execution status. The downstream functions get triggered immediately whenever data objects are ready to consume. Fig 8 (left) shows how the scheduler interacts with executors when running a workflow locally. The executors can synchronize the data status (e.g., readiness of local objects) with the scheduler, which then checks the associated bucket triggers and invokes downstream functions if triggering conditions are met. The low-latency message exchange between the scheduler and executors is enabled via on-node shared-memory object store.

The local scheduling policy makes decisions based on the status of executors. The scheduler only routes function requests to idle executors that have no running tasks, avoiding concurrent invocations and resource contention in each executor, similar to the concurrency model in AWS Lambda [8]. When the executor receives a request at the first time, it loads the function code from local object store and persists it in memory for reuse in subsequent invocations. The scheduler hence prioritizes executors with function code being loaded, in case of multiple idle executors. Note that, this work only considers warm executors, and how to deal with cold starts of executors is an active research area [30, 35, 41, 44, 55, 61, 67] but is out of the scope of this work.

Request’s delayed forwarding from overloaded nodes. If a scheduler receives many requests that exceed the capacity of local executors, it forwards them to other nodes. These requests are first sent to a coordinator, which then routes them to worker nodes with sufficient resources. Here, the coordinator does not immediately forward these requests. Instead, it delays this for a configurable short period of time, such that the functions can get executed locally in case any local executors become available. Executors may become available soon for handling delayed requests due to Pheromone’s microsecond-scale invocation overhead (see §6.2) and the typically short execution time of many functions [61]. In fact, this idea has been proven effective to enhance locality in cluster scheduling [73].

Inter-node scheduling. A coordinator not only forwards user requests from overloaded to non-overloaded nodes, more importantly it also drives the execution of large workloads. A large workflow needs to run across multiple nodes which collectively host its many functions. This cannot be locally orchestrated by individual schedulers without a global view.

As shown in Fig 8 (right), with inter-node scheduling, a coordinator gathers the associated bucket status of the functions of a large workflow, and triggers next functions potentially across nodes if triggering conditions are met. The data-centric orchestration makes Pheromone a natural fit to improving data locality in request scheduling. The coordinator makes the scheduling decision using the node-level knowledge reported by schedulers, including the number of idle executors and the number of data objects relevant to this workflow. It then schedules a request to the worker node that has sufficient executors with the most relevant objects.

4.3 Data Exchange Optimization

In addition to improving data locality in the distributed task scheduling (§4.2), Pheromone performs system-level optimizations for data exchange among both local and remote functions, where we trade the durability of short-lived, immutable intermediate data [48, 65] for low function interaction latency and low resource footprint.

Local data sharing. Pheromone leverages the shared-memory object store on each worker node to enable zero-copy data sharing among local functions (see Fig. 7). The intermediate objects are simply represented as byte arrays in the shared memory, such that functions can directly access them via the pointers (e.g., the function augments in Figure 5) without serialization overheads.

Inter-node data sharing. Pheromone allows the direct transmission of data objects between nodes. While using a remote storage system for inter-node data sharing could better ensure data durability and consistency [21, 62, 64], there is no such need for short-lived, immutable data objects (e.g., typical return values of a function). We thus avoid the unnecessary data copy for reduced network and storage overheads. Pheromone only synchronizes data objects with the durable key-value store when they are specified to persist (see ‘send_object()’ in Table 1).

Fig. 9 shows two inter-node data sharing mechanisms in Pheromone. By default, when requested Pheromone transmits data objects as raw byte arrays to avoid the serialization
overhead (see Arrow ‘a’ in Fig. 9), which significantly improves performance for large object transmission ($\S6.2$). In addition, Pheromone has a shortcut to transmit small data objects across nodes (e.g., smaller than 1KB, see Arrow ‘b’ in Fig. 9), where such small objects can be directly packed into the forwarded requests during the inter-node scheduling in §4.2. This avoids the function to additionally retrieve the required data objects from its upstream function. Moreover, Pheromone runs multiple I/O threads on each worker node to improve performance for inter-node data sharing.

4.4 Scalability

The key for Pheromone to achieve high scalability is to scale the distributed scheduling process ($\S4.2$). To enable this, we apply a shared-nothing model that significantly reduces synchronizations between local schedulers and global coordinators. Specifically, Pheromone partitions the workflow orchestration tasks across shared coordinators, each working on a disjoint set of workflows and needing not to synchronize with each other. When executing a workflow, the associated coordinator sends its data triggers to the selected worker nodes and routes the requests to them. They only share the data and trigger status with this associated coordinator, which substantially reduces the communication and synchronization overheads. This is achieved by running a standard cluster management service (e.g., ZooKeeper [4, 45]) that deals with coordinator failures and allows a client to locate the coordinator of a specific workflow. The client can then interact with this coordinator to configure data triggers and send requests. This process is automatically done by the Pheromone client library and is transparent to developers.

5 Implementation

The key components of Pheromone (Fig. 7) are implemented in 4.8k lines of code in C++ for delivering high performance and are packaged into Docker [16] images for ease of deployment. The client for developers is implemented in 400 lines of Python code. Pheromone runs on a Kubernetes [22] cluster for convenient container management. We use Anna [68, 69], an autoscaling key-value store, as the durable key-value storage and deploy it into the same cluster. In each worker node, we mount a shared in-memory volume between containers for fast data exchange and message passing. The executor loads function code as dynamically linked libraries, which is pre-compiled by developers and uploaded to Pheromone. We open source the entire Pheromone codebase at [23].

6 Evaluation

In this section, we evaluate Pheromone through cluster deployment in AWS EC2. Our evaluation is set to answer two questions: 1) How does Pheromone improve the performance of function interactions ($\S6.2$) and ensure high scalability compared with the current serverless platforms ($\S6.3$)? 2) Can developers easily implement various real-world applications with Pheromone and deliver high performance ($\S6.4$)?

6.1 Experimental Setup

Cluster settings. We deploy Pheromone in an EC2 cluster. The coordinators run in c5.xlarge instances, each with 4 vCPUs and 8 GB memory. Each worker node is a c5.4xlarge instance that has 16 vCPUs and 32 GB memory. The number of Executors in a worker node is configurable and we tune it based on the requirements of our experiments. We deploy up to 8 coordinators and 51 workers, and run clients in separate instances in the same us-east-1a EC2 zone.

Baselines. We compare Pheromone against four baselines.

1) Cloudburst: An open-source platform providing fast state sharing for Python functions, Cloudburst [64] employs function-collocated caches and allows low-latency function compositions. It uses Kubernetes for deployment and Anna [68, 69] as the remote storage. As Pheromone’s cluster setting is similar to Cloudburst’s setting, we deploy the two platforms using the same cluster configurations and resources.

2) KNIX: As an evolution of SAND [31], KNIX [21] improves the interaction performance by executing functions in a workflow as processes running in the same container, where small data transfer is facilitated through a local message queue. KNIX also provides a persistent remote storage (i.e., Riak [24]) for transferring large data.

3) AWS Step Functions (ASF): As a popular commercial serverless offering, we use AWS Step Functions with its Express Workflow enhancement [12] for the interactions among Lambda instances. As ASF has a size limit of transferring intermediate data (see Fig. 2), we deploy a Redis [5] cluster to enable sharing large data objects between functions.

4) Azure Durable Functions (DF): Compared with ASF, DF provides a more flexible support for function interactions, especially with Entity Functions [14], which allows developers to manage workflow states following the actor model [34, 52]. We include DF to study the performance of this approach.

Unlike Cloudburst and KNIX, we cannot control the orchestration runtime in the two commercial platforms, namely ASF.
and DF. To make a fair comparison, we configure Lambda and Azure functions such that their numbers match that of the executors in Pheromone. The resource allocations of each function and executor are also maintained the same.

### 6.2 Function Interactions

#### Function invocations under various patterns.

We first evaluate the overhead of invoking no-op functions without any payload. We consider three common invocation patterns: sequential execution (e.g., a two-function chain), parallel invocations (fan-out), and assembling invocations (fan-in). We vary the number of involved functions for parallel and assembling invocations to control the degree of parallelism. Fig. 10 shows the latencies of invoking no-op functions under the three patterns, broken down into the overhead of external and internal invocations. The former measures the delay between the arrival of a user request and the complete start of the workflow, and the latter measures the delay of internally triggering the downstream function(s) following the designated pattern. In Pheromone, the external invocation delay is mostly attributed to the network overhead of request routing, which takes about 200 µs [17]. Functions can be invoked locally or remotely in Pheromone and Cloudburst, which we respectively measure in Fig. 10.

Fig. 10 (left) compares the invocation delays of a two-function chain measured in five platforms, where Pheromone significantly outperforms the others. In particular, the low-latency message passing enables Pheromone to cut the local invocation delay to about 40 µs, which is 9× faster than Cloudburst. The latency improvements become more salient compared with other platforms, with 140×, 457×, and 1657× speedup over KNIX, ASF, and DF, respectively. When invoking a remote function, both Pheromone and Cloudburst require network transfer, leading to a similar internal invocation delay. Yet, Cloudburst incurs higher overhead than Pheromone for external invocations, resulting in worse overall performance.

Fig. 10 (center) and (right) show the invocation latencies under parallel and assembling invocations, respectively. We also evaluate the cross-node scenarios for Pheromone and Cloudburst by configuring 12 executors in each worker node, thus forcing remote invocations when running 16 functions. Pheromone consistently achieves the best performance, enabling microsecond-scale latency in any cases, even for cross-node function invocations. In contrast, Cloudburst leads to a much longer latency of external function invocation as the number of functions grows; both KNIX and ASF incur high invocation overhead in parallel and assembling patterns, where KNIX suffers the most in assembling. Among all four baseline platforms, DF yields the worst interaction performance. We thus exclude it from the following experiments.

#### Data transfer.

We next evaluate the interaction overhead when transferring data between functions. Fig. 11 compares the invocation latency of a two-function chain with various data transfer sizes in Pheromone, Cloudburst, KNIX, and ASF. We evaluate both local and remote data sharing for Pheromone and Cloudburst. For KNIX and ASF where data transfer can be facilitated using either workflow or shared storage (i.e., Riak and Redis), we report the best of the two choices. For local execution, Pheromone enables zero-copy data sharing, leading to extremely low overhead regardless of the object size, e.g., 0.1 ms for 100 MB data. In comparison,
We next evaluate the scalability of Pheromone in terms of both internal function calls and external user requests. For internal invocations, we focus on two common patterns: sequential and parallel executions.

**Long function chain.** We start with a long function chain that sequentially executes a large number of functions [72]. In this workflow, each function simply increments its input value by 1 and sends the updated number to the next, and the final result is the number of total functions. We evaluate the workflow on Pheromone, Cloudburst, KNIX, and ASF by varying the number of chained functions. Fig. 13 shows their latencies, where Pheromone can achieve the best performance at any scale. In particular, Cloudburst suffers from poor scalability, causing significantly longer latency when the function number increases; KNIX cannot host many function processes in a single container, making it ill-suited for such large workflow and failing to execute 1K chained functions; ASF leads to the long end-to-end latency due to its high overhead of function interaction. Compared with Cloudburst and ASF, Pheromone improves the latency by up to 191× and 453×, respectively.

**Parallel functions.** We next evaluate parallel executions on the four platforms. Fig. 14a compares their end-to-end latencies of invoking various numbers of parallel functions, where each function sleeps 1 second. We run 80 function executors per node in Pheromone and Cloudburst. Pheromone only incurs negligible delay in large-scale parallel executions, while ASF and Cloudburst cause much higher overhead, e.g., seconds or tens of seconds, significantly harming the performance. KNIX cannot support highly parallel workloads as it needs to run all parallel function instances in the same container. To further compare system behaviors in parallel invocations, Fig. 14b shows the distribution of function start time. In particular, Pheromone can immediately launch all the 4K functions within 40ms. ASF triggers functions at a slower speed, eventually needing around 3.8s to complete the invocations. Cloudburst performs the worst, needing around 56s to schedule 4K functions before actual invocations.

**Throughput.** We next study the scalability of Pheromone
In this section, we study three representative applications on Pheromone: a latency-sensitive application that simulates the real-time query for pandemic-related risk, Yahoo’s streaming benchmark for advertisement events [38], and a data-intensive analytical job such as the MapReduce sort.

**Real-time query.** To illustrate the applicability of Pheromone to latency-sensitive services, we take as an example the pandemic-related risk query, where it needs to handle a large number of requests that query risk levels of various locations in real time. We simulate the application with a three-function workflow: the first extracts the locations from user requests; the second locally searches cached data for the number of infected people in this area; the third sets the risk level, e.g., low or high, based on the number, and returns it to users. We implement this application on Pheromone and the other baseline platforms. Fig. 16 (left) compares their end-to-end latencies. Owing to low-latency function interaction, Pheromone leads to $3.5 \times$, $23 \times$, and $79 \times$ speedups compared with Cloudburst, KNIX, and ASF, respectively. Fig. 16 (right) shows the latency breakdown of Pheromone and Cloudburst, where Pheromone only incurs microsecond-scale overheads.

**Advertisement event stream.** We next study a stream processing application on Pheromone, ASF and DF, where Pheromone can achieve both the ease of deployment and high performance. This application processes advertisement events in three phases [38]: it first accepts and filters incoming advertisement events (e.g., click or purchase), then checks which campaign each event belongs to, and periodically counts the number of objects.

In experiments we observe that Cloudburst’s schedulers can easily become the bottleneck under a high request rate, making it difficult to fully utilize the executor resources. KNIX suffers from a similar problem that limits its scalability. While ASF has no such concern, it leads to low throughput due to high invocation overhead (Fig. 10). Compared with these systems, Pheromone ensures scalability with high throughput.

The key to porting this application to serverless platforms is ensuring the last aggregation task periodically performed on accumulated data, which can be simply enabled in Pheromone with the ByTime primitive (more details in Appendix). However, it is challenging for ASF, and we have to explore a ‘serverful’ workaround. We deploy the application as two separate ASF workflows, where the first handles all the tasks before the aggregation and the second only performs the remainder. The first workflow gets invoked every event and saves its result in Redis with a random key, which is then sent to an external, serverful coordinator (e.g., local machine). The coordinator needs to periodically trigger the second workflow using the accumulated keys, letting it access the actual data in Redis. Compared with ASF, DF can directly send data to a single, addressable Entity function for the aggregation [13]. Developers then periodically reset the function state and get the result. However, this approach suffers from very poor performance, making it ill-suited for such streaming applications.

To illustrate it, Fig. 17 shows the delays of accessing accumulated objects in the advertisement event stream when running on ASF and Pheromone. Lower delay and more objects are better.

**6.4 Case Studies**

Lower delay and more objects are better.
We compare Pheromone-MR when using a fast storage to exchange data. Therefore, server-with PyWren, when they share intermediate data via Redis. Running more (e.g., cluster size) for improved data exchange. Compared with Pheromone-MR, deploying a MapReduce program in PyWren is more complicated: we have to manually execute the two stages of functions (i.e., mappers and reducers) using its map operator, and explicitly transfer the intermediate data via a shared storage, e.g., Redis. Moreover, the storage engine needs to be carefully configured (e.g., cluster size) for improved data exchange.

We run a 10GB sort that generates 10GB of intermediate data. The Pheromone executor and Lambda instance are set to use the same resources, e.g., 1 vCPU. Fig. 18 compares the end-to-end latencies using various numbers of functions on PyWren and Pheromone-MR. We break down the latency into the interaction overhead and the time for compute and I/O. The former measures the delay between the completion of mappers and the start of reducers. For PyWren, the interaction overhead consists of two parts: the invocation delay of triggering all the reducers after mappers return, and the I/O latency when they share intermediate data via Redis. Running more functions in PyWren improves the intermediate data I/O, but causes longer latency in parallel invocations, making its overall interaction overhead increasingly dominant. Compared with PyWren, Pheromone-MR leads to significantly lower interaction delay, e.g., less than 1s, improving the end-to-end performance by up to 1.6×.

PyWren running atop Lambda falls behind Pheromone-MR due to two reasons. First, since AWS Lambda does not support its required execution pattern, i.e., large-scale map, it needs to implement this operation but in an inefficient way that incurs high invocation overhead. Moreover, Lambda has limited support for data sharing, forcing developers to explore external solutions, which causes high overheads even when using a fast storage to exchange data. Therefore, serverless platforms should support rich patterns of function executions while internally enabling fast data exchange, such that developers can easily and efficiently build serverless analytics frameworks. Unlike AWS Lambda, Pheromone can achieve all these requirements.

7 Related Work and Discussion

Data sharing in serverless. Data sharing is a common pain point in today’s serverless cloud. While many serverless-based execution systems leverage shared storage to enable and optimize data exchange among functions [36, 42, 43, 48, 54, 56, 57], other works exploit data locality to improve performance. For example, recent serverless platforms [46, 50, 51, 62, 64, 65] allow placing workflow functions in a single machine. OFC [53] and FaaS [59] provide autoscaling cache for individual applications. Shredder [78] and Zion [60] push function code into storage. Wukong [37] enhances the locality of DAG-based parallel workloads at the application level. Lambda [65] is a close work to Pheromone in that it makes the intents of function’s input and output explicit for improved locality. However, compared to Pheromone, it does not leverage data triggers to provide a unified programming interface for expressive and simplified function interactions, and its performance is heavily bound to OpenWhisk [2], a serverless platform without state-of-the-art performance [50].

Recent works on stateful serverless computing advocate low-latency access to mutable state [33, 62, 64, 76]. While Pheromone presumes that intermediate data are immutable, such mutable state can be enabled by leveraging Anna for data consistency in state sharing, like Cloudburst.

Optimizing function startup. A wide array of works have been proposed to reduce function startup latency and mitigate cold starts, including enabling fast provisioning of function instances [30, 35, 41, 55, 67] and improving function keep-live policies [44, 61]. These techniques for optimizing container-based serverless runtime can be applied to Pheromone.

8 Conclusion

This paper revisits the function orchestration in serverless computing, and advocates a new design paradigm that a serverless platform needs to: 1) break the tight coupling between function flows and data flows, 2) allow fine-grained data exchange among functions of a workflow, and 3) provide a unified and efficient approach for both function invocations and data exchange. With this data-centric paradigm, we designed a new serverless platform, called Pheromone, which achieves all the desirable properties, namely, rich expressiveness, high usability and wide applicability. Pheromone is open-sourced, and outperforms existing commercial and other open-source platforms by orders of magnitude in terms of latencies of function invocations and data exchange.
A Appendix

A.1 Function-Oriented Interface

In addition to configuring bucket triggers, Pheromone also provides a simplified interface for applications without the need of complex data consuming (e.g., a function chain). For these applications, Pheromone allows developers to simply describe the interaction patterns among functions using a function-oriented interface. The interface hides the details of data consuming, where developers only focus on functions and need not to configure triggers and specify buckets in object creation. Instead, these can be automatically done by Pheromone with the function-level knowledge.

A.2 Advertisement Event Stream

The function-oriented interface can be easily used to deploy the processing tasks on advertisement event steam. Fig. A.1 shows function interactions in this application, where the periodic data processing is backed by the ByTime primitive. We can simply describe it using the script in Fig. A.2. There are three functions that execute the three tasks (line 2), respectively. Their relationships are expressed as tuples, which specify the source and target functions and indicate how the data should be consumed. In particular, the query function is directly triggered to handle the output of preprocess (line 4), while the count get periodically triggered every 1 second using the accumulated data from the previous query (line 5). The application is simply deployed by registering its functions and dependencies (line 7-8).

A.3 MapReduce Framework

Data-centric function orchestration is well-suited for driving the execution of data-flow applications in an event-driven manner. We can easily build a MapReduce framework atop Pheromone, which we call Pheromone-MR. Pheromone-MR is backed by the DynamicGroup primitive.

Fig. A.3 gives an example of running the WordCount program atop Pheromone-MR, which works as follows. The framework first configures bucket triggers and accepts the code snippets of map and reduce from users, which are packaged into two Pheromone’s functions, respectively. The actual map functions execute the user-provided code and then automatically send out intermediate objects while indicating their targets in the names. Reduce functions thus get triggered to aggregate these objects and output the final results. Therefore, framework users can simply focus on the logic of the MapReduce program without needing to operate on specific intermediate objects.

Note that Pheromone-MR only needs 380 lines of C++ function wrappers and 120 lines of Python interface. Given that PyWren is programmed in about 6K lines of Python for exe-
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