**Abstract**

Developers are increasingly using function-as-a-service (FaaS) platforms for data-centric applications that primarily perform low-latency and transactional operations on data, such as for microservices or web serving workloads. Unfortunately, existing and recently proposed FaaS platforms support these applications poorly because they separate application logic, executed in cloud functions, from data management, done in interactive transactions accessing remote storage. This separation harms performance and makes it difficult to efficiently provide transactional guarantees.

We present Apiary, a novel DBMS-backed transactional FaaS framework for data-centric applications. Apiary tightly integrates application logic and data management, building a unified runtime for function execution and data management by wrapping a distributed database engine and its stored procedures. Apiary augments the DBMS with scheduling and tracing layers, providing a workflow programming interface for composing functions into larger programs with end-to-end exactly-once semantics, cross-function transactions, and advanced observability capabilities. In addition to offering more features and stronger guarantees than existing FaaS platforms, Apiary outperforms them by $2\times$ to $68\times$ on microservice workloads by greatly reducing communication and coordination overhead and using cluster resources more efficiently.

**1 Introduction**

Function-as-a-service (FaaS), or serverless, cloud offerings are becoming popular in both industry [8, 56, 66] and research applications [33, 62, 71]. FaaS developers write functions in high-level languages then compose them into larger applications containing many functions (e.g., using AWS Step Functions [10]). FaaS platforms radically reduce the operational complexity and administrative burden of cloud deployments, promising developers transparent auto-scaling and consumption-based pricing while eliminating the need to manage application servers [34].

FaaS is increasingly used for building data-centric applications: the low-latency and transactional applications such as a travel reservation web service or e-commerce microservices application that underlie much of the modern web. Unfortunately, it is fundamentally difficult for existing FaaS platforms to support these applications because platforms separate application logic, executed in cloud functions, from data management, done in interactive transactions accessing a remote database (Figure 1a). This causes two problems. First, it limits performance because state is externalized, so each operation on data must make a round trip to a remote storage system. Second, it makes providing transactional guarantees difficult because transactions may be arbitrarily re-executed and cannot span across functions [11, 27].

Recently, there has been much research on building FaaS platforms for data-centric applications to tackle these problems [19, 33, 62, 71, 73]. However, because these systems also separate function execution and data management, they struggle to provide both good performance and strong guarantees. Some, like Cloudburst [62], locally cache data to improve performance, but do not provide transactions. Others, like Boki [33] and Beldi [71], provide transactions using an external transaction manager bolted onto remote storage, increasing already-high storage access times by as much as $3\times$.

In this paper, we radically rethink the relationship between application logic and data management in FaaS platforms. We argue that since data-centric applications primarily perform transactional operations on data, FaaS platforms targeting these applications should tightly integrate function execution and data management (Figure 1b). To prove this, we propose Apiary, a transactional FaaS framework which provides a unified runtime for function execution and data management, delivering good performance and strong guarantees for data-centric applications. Apiary compiles each function in an application to a database `stored procedure` to make functions transactional and improve their performance. However, unlike traditional DBMSs, Apiary must support complex programs that require guarantees across many stored procedures, such as cross-function transactions and exactly-once function execution semantics. Thus, we design a novel scheduling layer for Apiary to compose and orchestrate stored procedures into larger programs while efficiently providing these guarantees.

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Designing a scheduling layer for Apiary is challenging because it must efficiently execute large FaaS programs comprised of many functions while providing cross-function transactions and exactly-once semantics, but existing DBMSs support neither composing stored procedures into larger programs nor providing guarantees across stored procedures. A naive solution is to run the entire FaaS program as one huge transaction in a conventional DBMS, but this causes unnecessary contention (e.g., holding write locks on a hotel reservation table while sending a confirmation email). Therefore, to efficiently support realistic FaaS programs in Apiary, we implement a programming interface for constructing complex programs as workflows of many functions with customizable transaction boundaries and build a fault-tolerant frontend service for executing workflows. To provide exactly-once semantics, we automatically instrument functions to transactionally record their executions in the DBMS so the frontend can safely re-execute them. However, naively instrumenting all functions is prohibitively expensive, degrading performance up to 2.2×. Therefore, we develop a novel algorithm to identify when functions can be safely re-executed, providing exactly-once semantics with <5% overhead.

Another useful benefit of Apiary’s design is that it simplifies a common problem faced by FaaS developers: obtaining observability into how applications interact with data. Developers need this information to debug, monitor, and audit their applications, for example to verify an application did not access private data. However, while existing FaaS platforms can trace function execution history, it is fundamentally hard for them to capture interactions with data because they lack visibility into how functions manage data, so developers must resort to expensive and error-prone manual logging across many short-lived functions. Critically, Apiary naturally has this visibility because it tightly integrates functions and data and can leverage existing techniques for database provenance capture. Therefore, we build in Apiary a tracing layer which traces application control flow across functions through workflow instrumentation, then records which data items each function accesses or updates through query instrumentation and change data capture to produce a complete history of application interactions with data. Obtaining this detailed information through manual logging incurs overhead of up to 92%, but our tracing layer reduces this to <15% by building a high-performance in-memory buffer and exporting its contents asynchronously.

We evaluate Apiary with commonly used microservice and e-commerce benchmarks such as social networking and e-commerce applications [24, 26]. We find that by tightly integrating function execution with data management and reducing communication overhead, Apiary outperforms the popular open-source FaaS platform OpenWhisk [49] by 7–68× and recent research systems like Cloudburst [62] and Boki [33] by 2–27×. Moreover, Apiary reduces the cost of deploying a FaaS application by 2.2–2.8× compared with OpenWhisk and Google Cloud Functions, even for a bursty time-varying workload, by using cluster resources more efficiently.

In summary, our contributions are:

- We demonstrate that the separation of function execution and data management in FaaS platforms makes it difficult to provide good performance and transactional guarantees for increasingly popular data-centric applications.
- We propose Apiary, a novel transactional FaaS framework for data-centric applications. By leveraging DBMS stored procedures to tightly integrate functions and data then composing them with a novel scheduling layer, Apiary provides transactional guarantees for functions as well as cross-function transactions and exactly-once semantics for workflows. Apiary also improves performance by 2–68× compared to existing FaaS platforms.
- We show that Apiary enhances observability by automatically instrumenting applications and their interactions with data, achieving <15% overhead as compared to 92% with manual logging.

## 2 Background and Motivation

### 2.1 Data-Centric FaaS Applications

Function-as-a-service (FaaS) platforms are increasingly used for low-latency and transactional data-centric applications such as microservices and web serving. Three example workloads, which we also use in our evaluation, include:

- **Shop**: An e-commerce service that allows customers to retrieve information about items, add those items to a virtual shopping cart, and check out those items [26].
- **Hotel**: A hotel reservation service that allows users to search hotels near a geographic location and reserve a room [24].
- **Retwis**: A social network service that allows users to post to a timeline and view and interact with other users’ posts [35].

Critically, much like other data-centric applications, all three workloads consist largely of short-lived tasks that primarily perform operations on data, such as saving a social network post, retrieving e-commerce item information, or reserving a hotel room. To make this point more concrete, in Figure 2 we break down the runtime of each application implemented with a conventional microservice architecture performing application logic in long-running RPC servers. As we can see, all three data-centric applications spend the vast majority of their runtime either communicating with the DBMS or executing DBMS operations; application logic other than DB operations accounts for only 1-7% of runtime.

### 2.2 Issues of Existing FaaS Platforms

Engineers want to implement data-centric applications using FaaS because it reduces the amount of infrastructure they need to manage. For example, in the traditional three-tier web serving architecture, engineers must manage both a stateful storage backend and a stateless middle tier of web servers that implement application logic and respond to client requests. Engineers are responsible...
for handling failures of any of these servers and for scaling them in response to changing load. FaaS promises to lift the burden of managing these servers, replacing the middle tier with functions implementing application logic and the backend with cloud storage while auto-scaling both functions and storage to reduce cost.

Unfortunately, existing FaaS platforms do not live up to this promise for data-centric applications. As we argued earlier, this is largely because existing platforms separate function execution from data management, causing several problems. Here, we detail two of them: performance overhead and transactional guarantees.

**Performance Overhead.** The data-centric applications we target typically perform low-latency operations on data, like point lookups and updates. In a high-performance in-memory DBMS, each of these operations takes at most a few tens of microseconds. However, as we show in Figure 3, in the popular FaaS platform OpenWhisk, as in other production FaaS platforms, they take more than a millisecond even if we ignore scheduling, container initialization, and other management overheads (which add an additional few milliseconds, analyzed in Section 7.5). For an OpenWhisk function to perform operations in a high-performance in-memory database, it must first establish a connection to the database (777 μs, this can be reduced by a connection pool but OpenWhisk does not support these natively), then issue queries remotely (340 μs round-trip time per query). These overheads are vastly greater than the actual query execution time of 23 μs for a point update. Thus, in conventional FaaS platforms, communication overhead decreases the performance of data-centric applications by an order of magnitude.

**Transactions.** Data-centric applications often require strong transactional guarantees and robust execution semantics. For example, if someone tries to reserve a hotel room, it is important that they pay for it exactly once and that no one else can simultaneously reserve the same room. Unfortunately, because FaaS platforms manage data using interactive transactions, they struggle to provide these guarantees. For example, if functions crash, existing platforms naively rerun them, potentially re-executing completed transactions. To avoid such problems, developers must implement workarounds like making all functions idempotent [11, 27] or building an external transaction manager [19, 71].

### 2.3 Current Approaches in Data-Centric FaaS

Many recent research projects seek to improve the performance and functionality of FaaS platforms on data-centric applications. A few of the most relevant to Apiary are Cloudburst [62], Boki [33], Shredder [73], and Beldi [71]. Cloudburst [62] proposes using the auto-scaling key-value store Anna [67] as a FaaS storage backend then improving data access performance with local caches. Boki [33] proposes a transactional FaaS storage backend based on shared logs that uses local caches to improve performance. Shredder [73] allows developers to define low-latency “storage functions” that run on the same server as a key-value store hosting their data. Beldi [71] bolts an external transaction manager onto existing serverless platforms to provide guarantees for workflows.

Unlike Apiary, none of these systems address the root cause of the issues of data-centric FaaS: the separation of function execution and data management. Thus, they struggle to provide both high performance and transactional guarantees. Beldi and Boki provide transactions, but require a costly external transaction manager; for example in Beldi this increases the overhead of remote cloud storage access by 2.4–3.3×. Cloudburst and Boki cache data locally to improve performance, but Cloudburst offers only causal consistency while Boki must frequently update caches to provide transactional guarantees, harming performance as we show in Section 7. Shredder runs functions on data servers, but offers no transactions and cannot distribute application data across multiple servers.

### 2.4 Non-Goals

Before discussing Apiary, we want to emphasize two objectives that are excluded from the scope of this paper.

**Compute-Heavy Workloads.** Apiary’s design focuses on short-lived data-centric applications, not long-running compute-intensive workloads such as video processing [23] or batch analytics [54]. These do not require Apiary’s features and guarantees, such as transactional functions and exactly-once semantics. If users wish to execute long-running tasks as part of an Apiary workflow, we expect them to leverage an external service, such as AWS Rekognition [9] for text detection in images.

**Non-Relational Data Models.** Apiary currently only supports a relational data model. We believe it is possible to extend Apiary to support transactional non-relational databases, such as MongoDB, but this is beyond the scope of this paper. Most comparable data-centric FaaS platforms are also restricted to relational or key-value data [19, 33, 58, 62, 71, 73].

### 3 Apiary Overview

To solve the challenges raised in Section 2, we design Apiary to tightly integrate function execution and data management. Apiary wraps a distributed DBMS, compiling functions to stored procedures so it can leverage the DBMS to build a unified runtime for both function execution and data management. A key implication of this design is that Apiary functions are simultaneously basic units of control flow and atomicity. Apiary leverages this visibility into control and data flow to aggressively co-locate compute and data and to augment the DBMS with scheduling and tracing layers providing transactions across function boundaries, exactly-once semantics for workflows, and advanced observability capabilities.
We sketch the Apiary architecture in Figure 4. It has three layers: the clients, frontend, and backend.

- **Clients**: Clients are end users interacting with Apiary. Users write functions and compose workflows using the Apiary programming interface, which we describe in Section 4.
- **Frontend**: Frontend servers route and authenticate requests from clients to the backend and implement the Apiary scheduling layer. Each server contains a dispatcher, which manages workflow execution, and a registrar, which handles workflow registration, instrumentation, and compilation. Neither component executes application logic; both are stateless and persistent state in the backend. We discuss both more in Section 5.
- **Backend**: The backend executes functions, manages data, and handles operational logging. It wraps a distributed transactional DBMS and its stored procedures. Apiary executes functions transactionally on DBMS servers and adds a tracing layer to automatically capture information on application-database interactions for observability, using a separate analytical DBMS to manage this data. We describe the backend in detail in Sections 5 and 6.

## 4 Programming Interface

Apiary gives developers an easy-to-use interface to build FaaS applications: they write functions in a high-level language and use SQL to access or modify data stored in a relational DBMS. Then, like in other FaaS platforms such as AWS Step Functions [10] and Azure Durable Functions [46], they can write high-level programs as workflows of many functions. Apiary executes functions as ACID transactions and provides cross-function transactions and exactly-once function execution semantics for workflows.

### 4.1 Function Interface

Apiary functions are written in a high-level language (we use Java) and take in and return any number of named serializable objects. Functions can embed any number of SQL queries to access or modify data in the DBMS. Apiary compiles functions to database stored procedures and guarantees they execute as ACID transactions. To enable static analysis (Section 5.4) and data tracing for observability (Section 6.2), Apiary requires all SQL queries in functions to be defined statically as parameterized prepared statements, a common requirement for database stored procedures. Additionally, to guarantee exactly-once semantics for workflows (Section 4.2), we require functions be deterministic and calls to external services (e.g., text detection) be idempotent, but we do not otherwise require functions be idempotent. We show the function interface in Figure 5 and sketch an example function in Figure 6.

```
void checkHotelAvailability() {
    int num = execQuery(query, inp.hotelID, dt);
    if (num < inp.numRooms) {
        avail = false;
        break;
    }
    avail = true;
    for (int dt = inp.start; dt < inp.end; dt++) {
        int num = execQuery(query, inp.hotelID, dt);
        avail = false;
        break;
    }
    returnOutput("availOutput", avail);
}
```

Figure 6: Implementing Check Hotel Availability from Figure 7 in Apiary. This function checks that a hotel has a room available for every night of a potential reservation.

Figure 7: The Apiary workflow for hotel reservation, which first checks a room’s availability then reserves it in one transaction, then sends a confirmation email to the user in a second transaction. Apiary guarantees both transactions execute exactly once.

## 4.2 Workflows

Realistic applications consist of many functions performing different operations. For example, for a hotel reservation service to book a room, it must verify the room is available at the given price, then book it, then send a confirmation email. In Apiary, developers can build these higher-level programs by constructing workflows of many functions. We sketch the workflow interface in Figure 5.

A developer constructs a workflow from a list of functions and a specification mapping outputs of earlier functions to inputs of later functions. Recursive or cyclic dependencies are not allowed. Each Apiary workflow has a single sink function that has no downstream functions, and its output is returned to the client. Thus, a workflow can be represented as a directed acyclic graph (DAG) where nodes are functions and edges are data flow. We sketch the workflow graph for our hotel reservation example in Figure 7.

Some applications require cross-function transactions, executing several functions in a larger workflow as one transaction. For example, in Figure 7, the first two functions (checking availability and reserving the room) must execute in one transaction to ensure the room is actually available when it is booked. Thus, Apiary allows users to designate a group of functions in a workflow as a single transaction, provided those functions form a connected subgraph of the workflow graph. Apiary compiles these functions to the same stored procedure and executes them in a single ACID transaction.

Many workflow applications require exactly-once semantics: the effect of a workflow execution must be equivalent to what it would be if each function executed exactly once. This guarantee is critical to support popular design patterns like sagas [12] and to provide reliable messaging. For example, in Figure 7, it is important to guarantee that a room is only booked once and that if it is booked successfully, a confirmation email is always sent. Providing exactly-once semantics efficiently is challenging because conventional DBMSs do not provide guarantees across separate
transactions and executing workflows as single transactions causes unnecessary contention (e.g., if the workflow in Figure 7 executes as a single transaction, it holds write locks on the hotel reservation table while sending a confirmation email). Apiary automatically provides exactly-once semantics for workflows by memorizing transaction outputs to enable safe workflow re-execution; to minimize overhead we leverage a novel algorithm to do this selectively. We discuss how we implement this guarantee in Section 5.4.

4.3 Discussion of Semantics

Apiary provides transactional guarantees for functions, cross-function transactions, and exactly-once semantics for workflows. Individual transactions are ACID, but entire workflows are not transactionally isolated from one another; transactions executed by concurrent workflows may be interleaved. This design gives developers flexibility to functionally execute related operations, but separate unrelated operations to avoid the performance overhead of excessively large or long-running transactions while still guaranteeing all operations execute exactly once.

Apiary’s guarantees are much stronger than those of commercial systems such as AWS Lambda or Azure Durable Functions, which provide neither transactions nor exactly-once semantics. They are also stronger than that of Cloudburst [62], which does not provide transactions or exactly-once semantics, although, unlike Apiary, it provides causal consistency for entire workflows. Apiary’s guarantees are similar to those of existing stateful FaaS workflow systems such as Beldi [71], Boki [33], and Transactional StateFun [19], which also provide transactions and exactly-once workflows. However, while these systems build costly external transaction managers over remote storage, Apiary instead minimizes transactional overhead by compiling functions to stored procedures.

5 Apiary Compilation and Execution

We implement the Apiary programming interface by wrapping a distributed DBMS. We compile functions to DBMS stored procedures then instrument and execute them, providing transactional functions, cross-function transactions, exactly-once function execution semantics, and data tracing for observability. Apiary builds on top of existing DBMSs so we can leverage their battle-tested infrastructure instead of designing a new data store from scratch. Apiary can be implemented using any distributed relational DBMS that has the following four properties:

• Supports ACID transactions.
• Supports running user code in a non-SQL language transactionally in stored procedures.
• Supports change data capture (for observability, Section 6.2).
• Supports elastic DBMS cluster resizing.

While many DBMSs have these properties (e.g., SingleStore [60] and Yugabyte [70]), we chose VoltDB [65] because we observed that data-centric workloads contain many El-Store-style [35] single-sited transactions, which VoltDB can execute efficiently.

5.1 Cluster Overview

An Apiary cluster is made up of a DBMS backend and an automatically-scaled number of stateless frontend servers that interface between clients and the backend. For isolation, we provide each application with its own backend, which consists of a distributed database whose servers are each located in their own container.

The Apiary backend relies on the DBMS for auto-scaling to reduce cost. For example, our implementation utilizes VoltDB’s elastic scaling capabilities, resizing each backend cluster using a utilization-based heuristic. We rely on DBMS auto-scaling because the data-centric applications we target are computationally bottlenecked by database operations. As we show in Figure 2, they spend 93-99% of their runtime communicating with the database or executing database operations. Thus, the separation of function execution and data management in other FaaS platforms is counterproductive: as we demonstrate in Sections 7.4 and 7.9, the communication overhead incurred by offloading application logic to another server harms performance and increases the cost of deployment.

5.2 Compilation

To improve performance and provide transactional guarantees, Apiary compiles each user function to a stored procedure, a routine in a non-SQL language that runs natively as a DBMS transaction. If a developer specifies that several functions should execute in a single transaction (Section 4.2), Apiary instead compiles them all to a single stored procedure. Compilation happens in two steps. First, Apiary instruments each function to capture application/database interaction information for observability (Section 6) and instruments each transaction to record its execution in the database for exactly-once semantics (Section 5.4). Then, Apiary registers the instrumented transaction in the DBMS. Many DBMSs support compiling functions from a high-level language into stored procedures; for VoltDB, this language is Java. Apiary extends the DBMS stored procedure interface, so we can compile any function that:

• Uses the Apiary interface (Figure 5) to communicate with the DBMS, receive inputs, and return outputs.
• Defines all SQL queries statically as parameterized prepared statements (to enable static analysis; this is a common requirement of DBMS stored procedures).
• Is deterministic and ensures all calls to external services (e.g., text detection) are idempotent and so can safely be re-executed.

Additionally, in our VoltDB-based implementation, because VoltDB can efficiently execute single-sited transactions, we have developers specify if a function (or multi-function transaction) is single-sited and, if so, which function input specifies the site.

5.3 Apiary Dispatcher and Workflow Execution

The Apiary dispatcher manages workflow execution. It executes each function or multi-function transaction in a workflow in topological order (executing independent transactions in parallel when possible), invoking the corresponding DBMS stored procedure, passing in its inputs, and collecting its outputs to send to later functions. We can pass function inputs and outputs through the dispatcher because, in our experience, they are typically small.

Apiary handles failures in function execution by aborting the containing transaction, then propagating a failure notification downstream. The Apiary dispatcher uses database-specific client code to retry transaction execution in case of recoverable or transient errors (e.g., the failure of a DB server that can fail over to a replica). If an
error is unrecoverable (e.g., a constraint violation or function runtime exception), Apiary utilizes the database to abort and roll back its containing transaction. Similar to other transactional serverless systems like Beldi, Apiary does not support nested transactions, so if a function aborts then Apiary aborts its containing transaction. After handling a failure, Apiary continues workflow execution but propagates a failure notification to all downstream functions; this enforces exactly-once semantics while giving developers control over how their workflows handle failures.

Because dispatchers must remember the outputs of earlier functions so they can pass them as inputs to later functions (as persisting them to the DBMS is expensive), failure of a dispatcher is nontrivial. We discuss in Section 5.4 how Apiary efficiently mitigates dispatcher failures by selectively persisting function outputs to provide exactly-once semantics.

5.4 Exactly-Once Semantics

As discussed in Section 4, Apiary guarantees exactly-once semantics for workflows: the effect of a workflow execution is equivalent to what it would be if each function executed exactly once. Two scenarios can lead to violation of exactly-once semantics: failures of DBMS servers and failures of Apiary dispatchers. Most distributed DBMSs can recover from failures of their own servers, typically using replication and logging. For instance, VoltDB can recover from any single server failure without loss of availability by failing over to a replica, and from failure of multiple servers without loss of data by recovering from logs.

To recover from dispatcher failures during workflow execution, Apiary must ensure a new dispatcher can resume from where the failed one left off. To make this possible, Apiary automatically instruments stored procedures to transactionally record transaction outputs in the DBMS before returning. Then, a new dispatcher can safely re-execute the workflow; each re-executed transaction first checks for a record from the earlier execution and if it finds one returns it instead of executing. This re-execution relies on two earlier-stated assumptions Apiary makes about functions: that they are deterministic and that all calls to external services are idempotent. Thus, if a dispatcher fails, any clients currently communicating with that dispatcher can send pending workflow invocations to another dispatcher, using a per-invocation unique ID to signal a re-execution. In case of client failures, Apiary can also record this unique ID and workflow metadata ahead-of-time in the database so dispatchers can automatically re-execute partially executed workflows without client involvement.

Our experiments (Section 7.7) show that naively recording every transaction output degrades performance up to 2.2× as it requires performing multiple additional database lookups and updates in each transaction. However, we can optimize this guarantee and reduce overhead to <5% (across all workloads we tested) by recognizing that some transactions can safely re-execute and need not be recorded. For example, if an entire workflow is read-only, it can be safely re-executed if its original execution failed, so we do not need to record any of its transactions. Therefore, we develop an algorithm (Algorithm 1) to determine, using static analysis when a workflow is compiled into stored procedures, which transactions must be recorded and which can be safely re-executed.

Algorithm 1 Selective Function Output Recording

```plaintext
1: function FINDRECORDEDTRANSACTIONS(W)
2:     \{t_1, ..., t_n\} = topSort(W) \quad \triangleright \quad t_1 \text{ is source, } t_n \text{ is sink.}
3:     Recorded = \{
4:     for \ t_x \in \{t_1, ..., t_n\} do \quad \triangleright \quad \text{Traverse from sink back to source.}
5:         if hasWrite(t_x) then
6:             Recorded.add(t_x)
7:         else
8:             \triangleright \quad \text{Use BFS to find all recorded transactions (or the sink)}
9:             \triangleright \quad \text{reachable without traversing a recorded transaction.}
10:             RT = BFSFindTxns(t_x, Recorded \cup \{t_n\}).
11:             if RT.size() > 1 then
12:                 Recorded.add(t_x)
13:     return Recorded
```

Figure 8: Example of Apiary’s selective recording rules. T3 is recorded as it performs a write. T1 must also be recorded to avoid inconsistent outputs to T2 and T3.

We must record any transaction performing a DBMS write to ensure writes are not re-executed (re-executing external calls is fine as they must be idempotent). Moreover, we must record a read-only transaction if there exist disjoint paths from it to multiple different recorded transactions, or to at least one recorded transaction and the sink. This guarantees that two recorded transactions which depend on a value computed by an ancestor will always observe the same value from that ancestor, even if workflow execution is restarted. To determine whether disjoint paths exist, we search for all recorded transactions (or the sink) reachable without traversing another recorded transaction; if there are more than one of these, there are disjoint paths and the transaction must be recorded.

We sketch our algorithm in Algorithm 1 and provide an example in Figure 8. T3 is recorded for performing writes, but T1 is also recorded despite being read-only. Suppose T1 was not recorded and a dispatcher crashed after executing T1 and T3. Upon re-execution, T1 may return a different value than it did originally because some data was changed by an unrelated transaction. If that happened, T2 would return an output based on the new output of T1, but T3 would return its recorded output based on the original output of T1. This causes an inconsistency that violates exactly-once semantics, so we must record T1 to prevent it.

**Correctness.** Our algorithm identifies a set of recorded transactions which guarantees exactly-once semantics: the effect of a workflow execution is equivalent to what it would be if each function executed exactly once. Recording extra transactions cannot provide stronger guarantees because in the absence of disjoint paths to different recorded transactions, a non-recorded transaction must have a single recorded transaction descendant which is the ancestor of all other recorded transaction (or sink) descendants and can provide a consistent output during failure recovery. We do not guarantee we find the minimal set of recorded transactions as semantic information about functions may obviate the need to record a transaction (for example, if we knew a function returned a constant to another
function, we could ignore that edge for this algorithm), but this is outside the scope of this paper.

**Complexity.** Because we traverse from the sink back to the source, we can memoize workflow graph search, so we only need to traverse each workflow graph edge once. Therefore, the time complexity of this algorithm is $O(V + E)$ where $V$ is the number of transactions and $E$ is the number of edges in the workflow graph. We only run this algorithm once per workflow, when the workflow is registered.

### 6 Observability

Developers often require information on how applications interact with data for debugging, monitoring, and auditing use cases, for example to verify an application did not improperly access private data. In existing FaaS platforms, this information is fundamentally difficult to collect because platforms lack visibility into how functions manage data, so developers must perform extensive manual logging across many short-lived functions. In this section we discuss how Apiary leverages its tight integration with the database to automatically record these interactions with minimal cost.

#### 6.1 Apiary Observability Interface

Apiary instruments workflows to trace the history of workflow and function executions, instruments queries to log database operations, and combines this information to create a complete record of application interactions with data. Specifically, Apiary records for each data item all function executions that accessed or modified it. Apiary automatically spools this information to an analytical database (in our implementation, Vertica [64]) for long-term storage and analysis. We use a separate analytical database because it is better optimized for large observability queries than a transactional DBMS. Long-term storage policies such as data retention rules are implemented by this database. Within the analytical database, information is organized into tables. For captured workflow information, we create a function invocations table per application:

```
FunctionInvocations (func_id, timestamp, function_name, workflow_name, execution_id)
```

*func_id*, the primary key, is a unique ID per function execution; all functions in a workflow invocation share the same *execution_id*. For each table used by an application, we create an event table for captured operations on that table:

```
TableEvents (timestamp, func_id, event_type, query, [record_data...])
```

*event_type* can be insert, delete, update, or read; *query* is the query string; *func_id* is a foreign key referencing FunctionInvocations.

The information stored in these tables enables efficient execution of useful observability queries for debugging, monitoring, and auditing FaaS applications, which we evaluate in Section 7.8.

#### 6.2 Implementing Observability

Apiary leverages its tight integration of functions and data to adapt database techniques like change data capture and query rewrites [6, 28] to a FaaS setting, efficiently capturing application interactions with data. When a function executes, Apiary adds an entry to FunctionInvocations. When a function performs a database operation, Apiary automatically records metadata such as the transaction ID to TableEvents. For write operations, Apiary also records updated data. For read operations, it modifies the query to return the primary keys of all retrieved rows (in addition to the requested information), then records them to identify each accessed record. To minimize overhead, we only capture rows that are actually retrieved, not rows that are accessed incidentally (e.g. by an aggregation that may access thousands of rows). However, we also log the queries themselves so this additional read information may be reconstructed later if it is needed for an investigation.

The challenge in capturing information on database operations is performing it efficiently while providing guarantees about what information is captured. To capture writes, we rely on DBMS change data capture to automatically and transactionally export information. However, read capture is more difficult, both because existing DBMSs do not have built-in read capture capability and because reads are numerous so overhead may be higher. We capture reads by instrumenting the Apiary *execQuery* function (Figure 5). We maintain a circular buffer inside each DBMS server’s memory. Whenever a read occurs in *execQuery*, we append its information to this buffer. Periodically, we flush the buffer to the remote analytical database. Our information capture is robust to function failure and re-execution because re-executions are recognized and deduplicated using their shared IDs. However, captured read information may be lost if the database server crashes while information is in the buffer; if developers cannot tolerate data loss, we can optionally place the buffer on disk to eliminate loss at some performance cost.

### 7 Evaluation

We evaluate Apiary with widely-used microservice and web serving workloads. We additionally use microbenchmarks to analyze the performance of Apiary’s features and guarantees. We show that:

1. By tightly integrating function execution and data management, Apiary improves data-centric FaaS application performance by 7–68x compared to production FaaS systems and 2–27x compared to recent research systems (Figures 9, 12).
2. By selectively instrumenting functions using a novel algorithm, Apiary provides exactly-once semantics for workflows with overhead of <5% compared to 2.2x for a naive solution (Figure 13).
3. By instrumenting database operations and function executions, Apiary automatically captures information on application-database interactions critical to observability with overhead of <15% as compared to 92% with manual logging (Figure 14).

#### 7.1 Experimental Setup

We implement Apiary in ~10K lines of Java code. We use VoltDB [65] v9.3.2 as our DBMS backend and Vertica [64] v10.1.1 as our analytics database. For communication between clients and frontend servers, we use JeroMQ [53] v0.5.2 over TCP.

In all experiments where not otherwise noted, we run on Google Cloud using c2-standard-8 VM instances with 8 vCPUs and 32GB DRAM. We use as a DBMS backend a cluster of 40 VoltDB servers with 8 VoltDB partitions per VM. For high availability, we replicate each partition once, as is common in production. We also use the same VoltDB cluster as the storage backend for our baselines. To ensure we can fully saturate this DBMS backend, we run 45 Apiary
frontend VMs and perform queries using 15 remote client VMs, each running on a c2-standard-60 instance with 60 vCPUs and 240GB DRAM. We spool observability data to a cluster of 10 Vertica servers running on a separate set of VMs from the VoltDB cluster. All experiments run for 300 seconds after a 5-second warmup.

7.2 Baselines

We compare Apiary to four baselines, ranging from production platforms to the latest research systems.

OpenWhisk. OpenWhisk (OW) [49] is a popular open-source production FaaS platform. We implement each of our workloads in the OW Java runtime, performing all business logic in an OW function but storing and querying data in an external VoltDB cluster. We coordinated with OW developers to tune our OW baseline. Since OW cannot efficiently manage multiple concurrent low-latency functions, we implement each workload in a single OW function. Additionally, we pre-warm OW function containers and only measure warm-start performance. In our experiments, we use 45 c2-standard-8 VMs as OW workers. To maximize OW performance, we use 5 controllers, each on a c2-standard-60 instance that manages 9 workers, load balancing between sub-clusters.

RPC Servers. Most microservices today are deployed in long-running RPC servers with separate application and DBMS server machines [24, 40]. We implement each of our workloads this way, running all business logic in RPC servers but storing data in an external VoltDB cluster. For fairness, we use the same communication library as Apiary (JeroMQ, chosen because we found it outperforms other libraries) and re-implement each microservice in Java following its original architecture, and use long-lived connections with the DBMS. In our experiments, we use a setup identical to Apiary but with all frontend servers replaced with RPC servers.

Boki. Boki [33] is a recent research system designed for transactional FaaS. We use Boki as a baseline because it is representative of a class of transactional workflow FaaS systems including Beldi [71] and Transactional StateFun [19], but is additionally co-designed with a log-based storage system with local caches for high performance. We use the experimental setup described in the Boki paper, deploying 8 storage nodes, 3 sequences, and 8 workers, each on an AWS EC2 c5d.2xlarge instance with 8 vCPUs and 16GB DRAM. We coordinated with the Boki authors to tune our baseline.

Cloudburst. Cloudburst [62] is a recent research system for stateful FaaS that provides causal consistency over data stored in the Anna [67] key-value store, improving performance with local caches. We choose Cloudburst as a baseline because it is an influential system which explicitly sets performant stateful FaaS as its goal. To maximize Cloudburst performance and ensure consistency of experimental results, we disabled its autoscaler and manually pinned function executors to every available worker thread. We otherwise run Cloudburst unmodified in its most-performant last-writer wins mode. Similar to the Boki setup and following recommendations from the Cloudburst authors, we deploy 1 Anna KV node, 4 scheduler nodes, and 8 worker nodes, each on an AWS EC2 c5.2xlarge instance with 8 vCPUs and 16GB DRAM.

For fairness, when comparing Apiary to Boki and Cloudburst, we use 8 VoltDB servers and 8 frontend servers.

| Workload | Operation     | Ratio | Read Only? | Access Rows | RPCs for # of # of SQL |
|----------|---------------|-------|------------|-------------|------------------------|
| Shop     | Browsing      | 80%   | Yes        | 8           | 2                      | 1 1                    |
|          | CartUpdate    | 10%   | No         | 1           | 2                      | 1 2                    |
|          | Checkout      | 10%   | No         | 5           | 6                      | 3 5                    |
| Hotel    | Search        | 60%   | Yes        | 30          | 4                      | 6 22                   |
|          | Recommend     | 39%   | Yes        | 1           | 2                      | 1 1                    |
|          | Reservation   | 1%    | Yes        | 5           | 2                      | 2 5                    |
| Retwis   | GetTimeline   | 90%   | Yes        | 550         | 3                      | 51 51                  |
|          | Post          | 10%   | No         | 1           | 2                      | 1 1                    |

Table 1: Microservice benchmark information. RPCs are for the RPC Servers baseline; Apiary and OW only require one client-server RPC. Apiary only requires one DB round trip per transaction, but the baselines require one per SQL query.

7.3 Microservice Workloads

We evaluate Apiary using three microservice benchmarks, each commonly used in previous microservices and FaaS papers. As we show in Table 1, these workloads cover a large design space for data-centric FaaS applications.

Shop. This benchmark, adapted from a Google Cloud demo [26], simulates an e-commerce service where users browse an online store, update their shopping cart, and check out items for purchase.

Hotel. This benchmark, from the DeathStarBench [24] suite, simulates searching and reserving hotel rooms. Our implementation contains a cross-function transaction similar to Figure 7, where validation and reservation are performed in the same transaction.

Retwis. This benchmark, from Redis [55], simulates a Twitter-like social network, where users follow other users, make posts, and read a “timeline” of the most recent posts of all users they follow. We use the same Retwis parameters as Cloudburst [62]; we create 1000 users, each following 50 other users, and pre-load 5000 posts.

7.4 End-to-End Benchmarks

We first compare Apiary performance with the OW and RPC Servers baselines on our three microservice workloads, showing results in Figure 9. For each benchmark, we vary offered load (sent asynchronously following a uniform distribution) and observe throughput and latency. For all three workloads, maximum throughput achieved by Apiary is greater for Shop (1.2M RPS) than Hotel (144K RPS) and for Hotel than Retwis (20K RPS). This is because most Shop operations access a single customer’s cart, while most Hotel operations look up data for several hotels and most Retwis operations access data for several dozen users (“Access Rows” in Table 1).

We find that Apiary significantly outperforms the RPC Servers baseline on two benchmarks and performs on par on the third – even though Apiary offers more features (like observability information capture) and stronger guarantees (like ACID functions and exactly-once semantics). Apiary outperforms the RPC Servers baseline due to reduced communication overhead: because it compiles services to stored procedures that run in the database server, it requires fewer round trips to perform database operations (Table 1). Moreover, Apiary eliminates RPCs between microservices because each service is implemented in Apiary functions. Apiary achieves 1.6–3.4× better median and tail latency than RPC servers on Shop and Hotel, where each transaction executes many database queries which each require an RTT in the baseline but not in Apiary. It
We measure from 2 to 40 database servers (16 to 320 data partitions), reference between Apiary

To further investigate the performance difference between Apiary and production FaaS systems like OW, we analyze OW performance on a microbenchmark of a single OW function that retrieves and increments a counter stored in VoltDB. We invoke this function 100K times and measure the average latency of each step.

Apiary dramatically outperforms OW on all three benchmarks. Due to a combination of scheduling, bookkeeping, container initialization, message passing, and communication overhead (analyzed in Section 7.5), Apiary improves throughput by 7–68× and median and tail latency by 5–14× compared to OW.

The results of these experiments establish that, for data-centric applications, separating function execution from data management is inefficient. A conventional FaaS platform not only requires the same number of long-running storage servers as Apiary to host and manage data, but also needs compute workers to run application logic. However, because the application logic of a data-centric task is computationally bottlenecked by database operations (as shown in Figure 2), these compute workers contribute little but add significant communication overhead. Thus, the tightly integrated architecture of Apiary reduces communication overhead, uses resources more efficiently, and, as we will show in Section 7.9, reduces the cost of deployment.

**Scalability.** We also evaluate the scalability of Apiary, measuring the maximum throughput Apiary can achieve with varying numbers of database servers. We show results for the Hotel benchmark in Figure 10, but obtained similar results for Shop and Retwis. We measure from 2 to 40 database servers (16 to 320 data partitions), beginning with 2 servers because each server needs a replica. We find that Apiary scales well; with larger numbers of servers, performance was mainly limited by VoltDB’s overhead of managing a large network mesh between servers.

**OpenWhisk Performance Analysis**

To further investigate the performance difference between Apiary and production FaaS systems like OW, we analyze OW performance on a microbenchmark of a single OW function that retrieves and increments a counter stored in VoltDB. We invoke this function 100K times and measure the average latency of each step.

As we show in Figure 11, OW adds significant overhead to a function invocation. Each invocation is first handled by a controller which performs basic operations such as bookkeeping and access control using function metadata stored in CouchDB (1 ms) before scheduling the invocation to an invoker/worker node (1.6 ms). OW uses Apache Kafka for controller-invoker communication, incurring 1 ms of round-trip latency. Once the invoker receives an invocation request, it needs to resume the execution of an already-warm container (1.4 ms). The function then executes in 1.1 ms. We emphasize that this high overhead is not unique to OW; other popular production FaaS systems have a similar architecture and performance characteristics. Apiary avoids this overhead because it integrates function execution and data management and stores all state in the backend DBMS, thus reducing communication overhead and avoiding expensive external state management.

**Comparing with Boki and Cloudburst**

We next compare Apiary performance with Boki and Cloudburst. As a benchmark, we use Retwis, chosen because both Cloudburst and Boki use it in their evaluation. Retwis is read-heavy, so to evaluate the performance impact of writes we evaluate a microbenchmark which retrieves and increments a counter associated with a key. We use 80K counters to minimize aborts due to write-write conflicts in Boki while still ensuring all counters fit into cache.
We find that our guarantee incurs overhead of <5%, but this low overhead is only possible because we use the algorithm to record selectively: only 25% of Shop, 0.25% of Hotel, and 0.2% of Retwis update its caches and enforce its snapshot isolation guarantee. Thus, we expect Boki to perform relatively better on read-heavy Retwis and relatively worse on the write-heavy microbenchmark, where most reads are non-local. Our experiments confirm this hypothesis.

Looking next at Cloudburst, we find that Apiary improves throughput by 5.2⇥ on Retwis and 27.7⇥ on the microbenchmark, with similar trends for latencies. The performance difference is surprising because both Apiary and Cloudburst perform all data access and updates locally, using stored procedures in Apiary and asynchronously-synchronized local caches in Cloudburst (though Apiary provides stronger guarantees than Cloudburst: ACID transactions versus causal consistency). Digging deeper, we find the performance difference comes largely from the more efficient implementation of Apiary: a read from a local cache in Cloudburst takes 300 µs as compared to <20 µs for a VoltDB read in Apiary (this adds up because Retwis contains several reads and Cloudburst does not batch them) and additionally Cloudburst incurs 2.2 ms of executor and scheduler overhead for each function execution as compared to 300 µs in Apiary.

7.7 Exactly-Once Semantics Performance Analysis

We now analyze the performance impact of the Apiary exactly-once semantics guarantee. As we discussed in Section 5.4, Apiary automatically instruments stored procedures to selectively record function outputs in the DBMS to guarantee consistency during failure recovery, using a novel algorithm to minimize recording overhead. We evaluate the overhead of our guarantee and compare it to a more naive implementation (similar to prior work [71]) that records all transaction executions, showing results in Figure 13. We find that our guarantee incurs overhead of <5%, but this low overhead is only possible because we use the algorithm to record selectively: only 25% of Shop, 0.25% of Hotel, and 0.2% of Retwis transaction executions must be recorded. By contrast, the naive implementation reduces throughput by 1.3–2.2⇥.

7.8 Enhancing Observability with Apiary

Data Tracing Performance Analysis. As we discussed in Section 6, to enhance observability Apiary automatically records application interactions with data, spooling captured information to an analytical database for long-term storage and analysis. To analyze the performance impact of this tracing, we measure Apiary performance with both read and write capture enabled, with only write capture, and with no capture. We also measure the performance of a “manual logging” baseline that represents how observability information is captured by application developers utilizing existing FaaS platforms: by manually logging to files on disk that are later exported by monitoring software like AWS Cloudwatch.

We show results for all experiments in Figure 14. We find that at low load, write capture has a negligible effect on latency but both read capture and manual logging increase latency (both median and tail) by up to 10%. At high load, write capture still has a negligible performance impact; read capture adds throughput overhead of up to 15% while manual logging adds overhead of up to 92%. Apiary data tracing overhead is low because we minimize the cost on the critical path, buffering captured observability data in the database’s memory and asynchronously exporting it in large batches.

Case Studies. We next evaluate the value and practicality of Apiary’s data tracing. We execute 150M Shop operations, generating 1.2B rows of traced data, and export this data to a single Vertica server, finding it compresses to just 12.4GB of disk space. We then use this dataset to show how Apiary can handle queries adapted from tasks of interest to our industrial partners [39]. Because these queries require information from multiple services plus the database, they are difficult to answer using existing FaaS platforms.

Debugging. Our first query is “What was the state of some record X when it was read by this particular function execution?” This query might be used to determine what input caused a function abort. Apiary can answer this query easily because it records in TableEvents all changes to data; we simply retrieve the last update to record X before the problematic function execution. Because function executions execute as serializable transactions, this is guaranteed to match the record state the function read. For instance, we can use a single SQL query to find the state of record X at a time TS:

```
SELECT record_data FROM TableEvents
WHERE event_type IN ('insert', 'update')
AND record_id=X AND timestamp <= TS
ORDER BY timestamp DESC LIMIT 1;
```

We execute this query on the largest event table in our Shop dataset (840M rows and 7GB storage) to find the exact state of a
record when it was retrieved by a particular Shop execution; the average query latency across five runs is 4.3 seconds. **Downstream Provenance.** Our second query is "Find all records that were updated by a workflow that earlier read record X." This query is useful for taint tracking, for example if record X contains misplaced sensitive information. We can answer this query in Apiary by scanning for functions that read record X, then returning the write sets of later functions in the same workflows:

```
SELECT DISTINCT(record_id)
FROM TableEvents AS T, FunctionInvocations AS F
WHERE T.event_type IN ('insert', 'update')
AND F.function_name in SUCCESSOR_FUNC_NAMES
AND F.execution_id in EXECUTION_IDS;
```

We execute this query on our Shop dataset to find all orders made by users who earlier browsed a potentially problematic item; the average query latency is 4.8 seconds across five runs.

### 7.9 Cost Analysis

Finally, we evaluate the cost of deploying Apiary to the cloud. In Table 2, we estimate the monthly total cost of serving the Shop workload (Hotel and Rewis trend similarly) on GCP for Apiary, OW, and RPC Servers. We also compare with a commercial FaaS platform using a serverless database: Google Cloud Functions backed by the serverless database Firestore [25]. We evaluate four different load patterns: low, medium, and high patterns consisting of a uniform 100 QPS, 10K QPS, and 1M QPS, plus a mixed pattern of 50% low load, 49% medium load, and 1% high load, representing diurnal variance with spikes. For all systems except GCF+Firestore (Firestore is pay-per-request and we exclude its storage cost), we provision the database cluster based on the peak load of the given query pattern and conservatively assume no DBMS scaling during the month. We assume OW can dynamically scale its workers and controllers to minimize cost at a given load, RPC Servers can scale its stateless microservice workers, Apiary can scale its stateless frontend servers, and GCF and Firestore are pay-per-request.

As expected, we find that Apiary minimizes cost compared to both OW and RPC Servers because it reduces communication overhead and uses resources more efficiently. Even though our analysis conservatively assumes Apiary does not scale its database, we find OW and GCF+Firestore are actually costlier than RPC Servers or Apiary. At low load, OW is on par with Apiary and GCF+Firestore is cheaper because it can scale to near zero cost. However, at medium and high load OW is 8.9–58.7× costlier and GCF+Firestore is 12.2–71.7× costlier because their high overhead, documented in earlier sections, means they require far more resources than Apiary to support the same load. Even for mixed load, OW is 2.8× costlier and GCF+Firestore is 2.2× costlier because this overhead outweighs any benefit derived from separating function execution and data management. Therefore, in a realistic web serving scenario, Apiary not only is faster and provides more features, but is also more cost-efficient than comparable systems.

```
| System    | Low Load 100 QPS | Mid Load 10K QPS | High Load 1M QPS | Mixed Load |
|-----------|------------------|------------------|------------------|------------|
| OW + VoltDB | $1,221           | $16,312          | $1,521,253       | $34,986    |
| RPC S. + VoltDB | $917           | $1,831           | $36,204          | $12,888    |
| GCF + Firestore | $204         | $18,595          | $1,857,859       | $27,792    |
| Apiary + VoltDB | $917          | $1,526           | $25,915          | $12,635    |
```

Table 2: Estimated monthly total cost for OpenWhisk, RPC Servers, Google Cloud Function (GCF) with Firestore, and Apiary serving the Shop workload on GCP, under different loads.

### 8 Discussion

We now describe potential future directions for Apiary that further explore tight integration with the DBMS to solve problems that are difficult in existing systems, then discuss how future DBMSs could better support FaaS programming models.

#### 8.1 Possible Extensions

**Privacy.** Laws such as GDPR mandate that personally identifiable information (PII) can only be used for certain purposes and must be deleted upon request [52]. There has already been much work on using DBMSs for privacy [32, 57], and we believe the tight integration of data management with function execution in Apiary can simplify the development of end-to-end privacy-preserving features. For example, using DBMS access control, a function could be associated with specific purposes and its access to application tables restricted based on those purposes. Moreover, using Apiary observability capabilities (Section 6), organizations could audit and monitor applications for privacy violations.

**Self-Adaptivity.** There has been much recent research on applying machine learning (ML) to systems problems, including scheduling [43], database index construction [36, 38], and DBMS configuration and tuning [63, 72]. A common challenge in these systems is collecting the data (e.g., system traces) needed for ML models and inference. By leveraging tight integration of function execution and data management, we can extend Apiary to capture more detailed information on both system and application behavior.

### 8.2 DBMS Support for FaaS

**Multi-Tenant Databases.** Currently, Apiary isolates applications by running each application in its own backend. However, we may potentially increase resource utilization by running different applications in a multi-tenant database. This requires solving two challenges. First, performance isolation: leveraging prior work on fair scheduling in multi-tenant systems [17, 59] and real-time databases [1, 30] to ensure all FaaS applications receive only their fair share of cluster resources. Second, security isolation: leveraging sandboxing research [2, 69, 73] to isolate stored procedures containing arbitrary user code from one another and from the database.

**Cross-Datastore Transactions.** Apiary provides good performance and strong guarantees for applications accessing a single data store, but some applications access multiple data stores, for example a relational database like Postgres plus a text search system like Elasticsearch [40]. In principle, Apiary could be extended to support multi-datastore backends, where some functions access one data store and other functions access another. However, this requires cross-datastore transactions so that functions accessing different data stores could be grouped into a single transaction. There

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1 Prices were retrieved from the Google Cloud Pricing Calculator on 2022-04-11, using the us-west1 region as it was the cheapest: https://cloudpricingcalculator.appspot.com/.
has been much work on cross-database transactions, but much of it either requires data stores to implement restrictive interfaces such as XA or is limited to specific APIs like key-value stores [20]. We would benefit from a more general solution.

9 Related Work

Data-Centric FaaS Platforms. Many recent research projects seek to improve the performance and functionality of FaaS platforms on data-centric applications. We have already discussed several related systems, including Cloudburst [62], Boki [33], Shredder [73], and Beldi [71], in Section 2. Similar systems to Boki and Beldi include AFT [61], which interposes between a FaaS platform and a remote data store to enforce read atomicity, and Transactional StateFun [19] which adds transactions to Apache Flink’s State-Fun [22] and supports either strong consistency with two-phase commit or eventually consistent workflows with sagas, though unlike Apiary both systems separate functions from data storage. Also related are FaaSIM [58], which allows functions to share memory regions, and LambdaObjects [44] which co-locates FaaS storage and compute, though unlike Apiary neither supports transactions.

Recent systems such as Hydrocache [68] and FaaSTCC [41], have proposed providing transactional causal consistency (TCC) for an entire FaaS workflow. This provides stronger isolation between workflows than Apiary because Apiary only provides transactional guarantees for individual functions and cross-function transactions. However, it provides weaker isolation between functions; these systems only provide TCC and thus allow anomalies such as stale reads and write-write conflicts, while Apiary provides serializable isolation for functions and cross-function transactions.

Another set of relevant systems include Pocket [37], Locus [54], and Sonic [42], which propose multi-tier cloud storage backends designed for FaaS applications. These systems are largely designed for compute-intensive tasks on large amounts of data (e.g., batch analytics) and trade off transactions and low latency for data storage cost. However, this tradeoff is not suitable for data-centric applications, which access smaller amounts of data but demand the low latency and strong transactional guarantees of Apiary.

Recently, cloud providers have released several serverless cloud database offerings, including Amazon Athena [7] and GCP Cloud Firestore [25]. There have also been recent research systems in this space, like Starling [50]. These systems allow developers to store and query data without managing sever deployments. However, unlike Apiary or other FaaS platforms, they can only execute SQL queries on data and cannot perform general-purpose computation.

Data Tracing for Observability. Apiary’s tracing layer is related to prior research on workflow provenance [31] and data provenance [15]; for example, we use query rewrites [6, 28] to capture data accesses. Workflow provenance traces the flow of data through different modules (e.g., functions) in a larger program, but assumes each is stateless. Data provenance traces the origin of individual data items, which models the state operations of a program, though tracing fine-grained data provenance is out of scope for Apiary.

The key challenge in tracing application interactions with data is capturing control flow information and linking it to data operations. Most existing systems rely on manual annotation, but some have proposed automatically capturing provenance information through kernel interposition [47] or dynamic analysis [48], though this information by itself is often too low-level for users [21, 51] so it must be supplemented with information from manual annotations [5, 21, 45, 47, 51]. Other systems have proposed automatically combining workflow and data provenance for scientific and analytics applications [4, 16], but tolerate high latencies. Apiary interposes between functions and the DBMS and leverages control flow information inherent in its FaaS programming model to automatically capture both workflow provenance and data operations without manual annotations. While prior systems provide information flow control-based security for FaaS [3], and secure container-based FaaS applications by tracing system calls and network activity (and using these to infer data movement) [18], we do not know of any prior work which can produce a similarly complete record of application interactions with data in a FaaS environment.

In-Database Computation. Many DBMSs can run procedural code as either user-defined functions (UDFs) or stored procedures [29]. UDFs are pure functions that cannot modify persistent state but can be invoked from within SQL queries. Stored procedures are less restrictive and can run arbitrary procedural code as part of a database transaction. Apiary therefore compiles user functions to database stored procedures to run them natively as performant transactions on database servers. While many DBMSs support running user code natively in stored procedures, to our knowledge none support composing them together into larger programs with end-to-end guarantees and tracing like Apiary.

10 Conclusion

We presented Apiary, a novel transactional FaaS framework for data-centric applications. Apiary is the first system to tightly integrate function execution and data management in a FaaS context, breaking with the convention of separating them. By wrapping a distributed DBMS and its stored procedures with new scheduling and tracing layers, Apiary gives developers a familiar FaaS workflow programming interface for composing functions into larger programs while also guaranteeing functions run as ACID transactions, providing cross-function transactions and end-to-end exactly-once semantics for workloads, and offering advanced observability capabilities. In addition to offering more features and stronger guarantees than existing FaaS platforms, Apiary outperforms them by 2–68x on microservice workloads by reducing communication and coordination overhead and using cluster resources more efficiently.

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