StreamBox-TZ: A Secure IoT Analytics Engine at the Edge

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Abstract
We present StreamBox-TZ, a stream analytics engine for an edge platform. StreamBox-TZ offers strong data security, verifiable results, and compelling performance. StreamBox-TZ isolates the data and its computations in a trusted execution environment (TEE) on the edge, shielding them from the remaining edge software stack which we deem untrusted. StreamBox-TZ addresses two major challenges: (1) executing high-throughput, low-delay stream analytics in a single TEE, which is constrained by a low trusted computing base (TCB) and limited physical memory; (2) verifying execution of stream analytics as the execution involves untrusted software components on the edge. StreamBox-TZ contributes a data plane designed and optimized for a TEE on the edge. It supports continuous remote attestation for analytics correctness and result freshness while incurring low network bandwidth overhead. Built on ARM TrustZone, StreamBox-TZ only adds 42.5 KB executable to the trusted computing base (16% of entire TCB). On an octa core ARMv8 platform, it processes input events up to 140 MB/sec (12M events/sec) with sub-second delay, outperforming popular engines by one order of magnitude in throughput. The overhead incurred by StreamBox-TZ’s security mechanism is less than 25%.

1. Introduction
Internet of things (IoT) produces a large influx of streaming data. For instance, in each day a power sensor may produce 140 million samples [16] and a single refinery may produce 1TB of data [81]. Such enormous data must be processed in time. The high cost and long delay in sending IoT data to data centers necessitate edge processing [88,90]. Sensors send data to nearby gateways dubbed “cloud edge”; the edge runs a pipeline of continuous computations to cleanse and summarize the IoT data and sends results to data centers for deeper analysis. Edge is often optimized for cost and efficiency. According to a 2018 survey [43], modern ARM machines are typical choices for edge platforms. Such a platform often has 2–8 CPU cores and several GB DRAM. On an edge platform, recent analytics software show promises to process millions of events per second while keeping processing delays under one second [16,17,75,82].

Yet, edge processing challenges data confidentiality and integrity, two pressing concerns for IoT. On one hand, the edge faces existing threats to IoT security, including lack of professional supervision [55,105], weak configurations [97,104], and long delays in receiving security updates [55,101]. On the other hand, the edge’s architecture and role further amplify these threats. i) The edge exposes a much larger attack surface than IoT sensors. It processes data with a sophisticated software stack, which typically consists of a runtime framework called a stream analytics engine [37,42,76,82,107], rich user libraries [41,45,56], and a commodity OS. Each of these components often consists of hundreds of thousands of SLoC, for which misconfiguration [106] and vulnerabilities are not uncommon [23,35]. ii) For cost saving, edge processing jobs may co-run with untrusted programs. For instance, an agriculture IoT deployment is reported to run edge analytics on the farmers’ mobile computers [101]. iii) As the edge aggregates data from many sources, it incentivizes attackers. Once attackers compromise the edge, they not only obtain confidential data from multiple sources (e.g. a smart farm’s pest activities from all monitors) but also may delete or fabricate data sent to the cloud (e.g. silently dropping alarming pest events), threatening the integrity of entire IoT deployment.

Our goal is to safeguard IoT data in high-throughput and low-delay analytics on an edge platform and ensure correct and timely analytics outcome. We advocate isolating streaming data and computations in a trusted execution environment (TEE), shielding them from the remaining edge software stack which we deem untrusted. We isolate the edge’s trusted computing base (TCB), limit its interfaces, and shrink it from the whole software stack to only the TEE and the CPU hardware, hence significantly enhancing data security.

We face three challenges: i) what functionalities should be protected in TEE and behind what interfaces? ii) how to execute stream analytics on a TEE’s low TCB and limited physical memory while still delivering high throughput and low delay? iii) as both trusted and untrusted edge components participate in stream analytics, how to verify the outcome? No solution is available: pulling entire stream analytics engines to TEE [22,27,33] or partitioning them as-is [66,84] would result in a larger TCB with a wide
Figure 1: An overview of StreamBox-TZ

Our response is StreamBox-TZ, a stream analytics engine simultaneously offering strong data protection, verifiable outcome, and compelling performance on an edge platform. StreamBox-TZ builds on ARM TrustZone [2]. As shown in Figure 1, StreamBox-TZ contributes the following notable designs:

1. **Architecting a data plane for protection** StreamBox-TZ provides a data plane exposing narrow, shared-nothing interfaces to untrusted software. The data plane encloses i) all analytics data; ii) a library of stream algorithms called trusted primitives as the only allowed computations on the data; iii) key runtime functions, including memory management and cache-coherent parallel execution of trusted primitives. It leaves thread scheduling and synchronization out of TEE.

2. **Optimizing data plane performance within a TEE** In contrast to many TEE-oblivious stream engines that normally operate on numerous small objects, hash tables, and sophisticated memory allocators [31,89,107], the data plane embraces unconventional choices of algorithms, data structures, and optimizations. i) It implements trusted primitives with array-based algorithms and optimizes them with handwritten ARMv8 vector instructions [21]. ii) It uses contiguous, virtually unbounded buffers called uArrays to encapsulate all the analytics data; it backs uArrays with on-demand paging in TEE and manages uArrays with a specialized allocator. The allocator leverages hints from the untrusted control plane for data placement. iii) It exploits TrustZone’s unique, lesser-explored hardware features: ingesting data straightly through secure IO without a detour through the untrusted OS; avoiding relocating streaming data by leveraging the large virtual address space dedicated to TEE.

3. **Verifying edge analytics execution** StreamBox-TZ supports cloud verifiers to attest analytics correctness, result freshness, and hints supplied by the control plane during execution. Agnostic to the high-level pipeline being executed, the data plane captures coarse-grained dataflows and accordingly generates audit records. The cloud verifier replays the audit records for attestation. To minimize overhead in edge-cloud uplink bandwidth, a precious resource in many IoT scenarios [77,101], StreamBox-TZ compresses the records by up to 6× with domain-specific columnar encoding.

Our implementation of StreamBox-TZ supports a generic stream model [1] with a broad arsenal of streaming operators. The TCB of StreamBox-TZ contains as little as 267.5 KB of executable code, of which StreamBox-TZ only constitutes 16%. On an octa core ARMv8 platform, StreamBox-TZ processes up to 12M events (144 MB) per second at sub-second output delays. Its throughput on this platform is an order of magnitude higher than an SGX-based secure stream engine running on a small x86 cluster with richer hardware resources [31]. The security mechanisms contributed by StreamBox-TZ incur less than 25% throughput loss; decrypting ingress data, when needed, incurs 4%–35% throughput loss. While sustaining high throughput, StreamBox-TZ uses up to 130 MB of physical memory in most benchmarks.

The key contributions of StreamBox-TZ are: i) a stream engine architecture with strongly isolated data and a low TCB; ii) a data plane built from the ground up with computations and memory management optimized for a single TrustZone-based TEE; iii) remote attestation for stream analytics on the edge and domain-specific techniques for compressing audit records. To our knowledge, StreamBox-TZ is the first system designed and optimized for data-intensive, parallel computation inside one TEE. Beyond stream analytics, the StreamBox-TZ architecture should help secure other important analytics on the edge, e.g., machine learning inference. The StreamBox-TZ source will be made publicly available.

2. **Background & Motivation**

This section presents the background on ARM hardware and stream analytics. It describes security threats and then motivates our threat model and objectives.

### 2.1 ARM for Cloud Edge

As typical hardware for IoT gateways [43], recent ARM platforms offer competitive performance at low power, suiting edge well. Most modern ARM cores are equipped with TrustZone [2], a security extension for TEE enforcement. TrustZone logically partitions a platform’s hardware resources, e.g., DRAM and IO, into a normal (insecure) and a secure world. The secure world is often governed by a TEE.
Operator

An event A window

Ingress Windowing Aggregation Egress GroupBy

< power, plug, house, time >
< window, house >
< plug, power >
< window >
< house, power >

Stream analytics engines Stream pipelines are executed by a runtime framework called a stream analytics engine [27, 42, 44, 75, 76, 82]. A stream analytics engine consists of two types of function: data functions for data move and computations; control functions for resource management and computation orchestration, e.g., creating and scheduling tasks. The boundary between the two is often blurry. To amortize overheads, control functions often organize data in batches and invoke data functions to operate on the batches.

2.3 Security Threats to Edge Processing

Edge platforms face common security threats in IoT deployment. First, IT expertise is weak. Edge platforms are likely managed by field experts [55, 101, 105] rather than IT experts. Such lack of professional supervision is known to result in weak configurations [97, 104]. Second, the infrastructure is weak. Deployed in the field, the edge often experiences slow uplinks [77, 101] and hence much delayed software security updates. For cost saving, edge analytics may need to share OS and hardware with other high-risk, untrusted software such as web browsers [101].

Besides the above threats to IoT data, current edge processing significantly widens the attack surface by exposing the data to an analytics software stack that is much larger and more complex than IoT sensor software. This is illustrated in Figure 3(a). Of the software stack, a modern stream analytics engine contains a large code base (e.g., 22K for a research prototype [75] and around 550K for two production engines [19, 44]). Such an engine depends on external third-party libraries, such as Intel TBB (88K SLoC) [56] for parallel algorithms and Facebook folly (200K SLoC) [45] for efficient data structures. Many popular engines [19, 82, 107] further depend on modern language runtimes such as Go (94K SLoC) and JVM (∼1.2M SLoC).

Beneath the userspace is a commodity OS kernel containing millions of SLoC [103]. It is difficult for such a sophisticated software stack to provide strong security guarantees. User libraries and runtimes commonly see exploitable vulnerabilities [3, 5, 23, 38]. Commodity OS kernels are known to be vulnerable [35] and considered untrusted in recent research [56, 52, 72, 73]. A successful attacker compromising any layer in the software stack gains full data access.

2.4 Threat Model & Design Objectives

IoT scenarios We target an edge platform in an IoT scenario for capturing and analyzing data. We recognize the significance of mission-critical IoT with tight control loops, but do not target it. Our target scenario includes source sensors, edge platforms, and a cloud server which we dub “cloud consumer”. All the raw IoT data and analytics results are owned by one party. The sensors produce trusted events, e.g., by using secure sensing techniques [47, 68, 87]. The cloud con-

/* 1. Declare operators */
Ingress in /* config info */;
Window w(1 _SECOND ); GroupBy house > gb;
Aggregation<house, win> ag; Egress out;
/* 2. Create a pipeline. Connect operators */
Pipeline p; p.apply (in);
in.connect (w). connect (gb).
connect (ag). connect (out);
/* 3. Execute the pipeline */
Runner r ( /* config */ ); r.run (p);

Figure 2: Simplified pseudo code declaring the above pipeline

Figure 2: Example stream data, operators, and a pipeline
Figure 3: Among alternative architectures for secure stream analytics, StreamBox-TZ (d) leads to the smallest TCB and the most optimized data plane. Arrows indicate data flows.

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Why are existing systems inadequate? These challenges are unaddressed in prior work. First, many TEE-based systems \((22, 27, 33)\) pull entire user applications and libraries to the TCB, as shown in Figure 3(b). However, as we described in Section 2.2, a modern analytics engine and its libraries are large, complex, and potentially vulnerable. Second, partitioning applications as-is to a TEE, as shown in Figure 3(c) \((66, 91)\), does not apply to existing stream engines: their data structures mismatch small memory and delay, i.e. result freshness. It is therefore crucial to verify these properties.

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Third, verifying analytics results. Although the control functions and the OS are kept out of TEE, their behaviors, e.g. job dispatch, nevertheless affect analytics correctness and delay, i.e. result freshness. It is therefore crucial to verify these properties.

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Figure 4: StreamBox-TZ on an edge platform with ARM TrustZone. Bold arrows show the protected data path.

**Data plane & design choices** The data plane consists of only a library of stream computations called trusted primitives; and a runtime for trusted primitives.

In response to the aforementioned architecting challenge, we make the following choices specifically. i) Trusted primitives are stateless, single-threaded building blocks for declarative operators, shown in Table 1. The data plane eschews exporting interfaces for executing whole operators: as one operator instance has internal thread-level parallelism, doing so would pull thread management to the data plane and hence add substantial complexity. Although exporting low-level trusted primitives entails more TEE switches, the costs are becoming lower on modern ARM [25, 53] and can be further amortized by data batching, as will be discussed soon. ii) The runtime only incorporates functions critical to TEE integrity or performance: TEE memory management and paging, which are keys to TEE integrity; cache coherence of parallel primitives, which is key to parallelism.

Executing only the low-level primitives, the data plane is agnostic to declarative operators and the pipeline being executed. As StreamBox-TZ downloads and launches new pipelines, the data plane remains sealed as long as all primitives required by the new pipeline are already enclosed in the primitive library. We will present trusted primitives in Section 4 and memory management in Section 5 which address the challenge to data plane optimization.

**Control plane** The control plane runs stream analytics programmed as a pipeline of declarative operators. It creates plentiful parallelism among and within operators. It elastically maps the parallelism to a pool of threads it maintains. At a given moment, all threads may simultaneously execute one operator as well as different operators over different data.

### Table 1: Selected trusted primitives (columns) and selected declarative operators (rows) they constitute. Currently StreamBox-TZ includes 23 trusted primitives, capable of assembling most operators in commodity engines [19][107].

| Protected data path | Streaming data & State data |
|---------------------|----------------------------|
| Mem mgmt            |                             |
| Audit Log           |                             |
| Trusted Primitives  |                             |
| Operator Pipeline   |                             |
| Job dispatch; Thread scheduling; Synchronization; Perf monitoring… |
| Libraries glibc, libstdc++, Boost, libzmq … |

**High-Lv Operators**
- Sort
- Merge
- Segment
- SumCnt
- TopK
- Concat
- Join
- GroupBy
- Windowing
- AvgPerKey
- TopKPerKey
- TempJoin

**This work**

4. **Trusted Primitives and Optimizations**

StreamBox-TZ’s data plane provides trusted primitives as the only allowed computations over the protected data. These primitives are generic enough: they can be composed to implement most operators of commodity engines such as Spark Streaming [107] and Flink [19], and to implement non-trivial pipelines as will demonstrated in Section 8. Table 1 lists selected primitives and some common operators they form.

**Parallel execution inside a TEE** A trusted primitive instance is single-threaded and oblivious to synchronization. To exploit task parallelism, the control plane invokes multiple primitives from multiple worker threads, which then enter the TEE to execute the primitives in parallel. All trusted
primitives share one cache-coherent memory address space in TEE, which greatly simplifies data sharing and avoids copy cost. This contrasts to existing TEE-protected analytics engines that lack a cache-coherent shared address space on a multicore machine [51, 89].

**Array-based algorithms to suit TEE** We strongly favor algorithms with simple logic and low memory overhead, despite that they may incur higher algorithmic complexity. Corresponding to contiguous arrays as the universal data containers in TEE, most primitives use sequential-access algorithms over contiguous arrays, e.g., executing Merge-Sort over event arrays and scanning the resultant array to calculate the average value per key. Our choices of array-based algorithms contrast to many popular stream engines that use hash-based algorithms for lower algorithmic complexity.

**Vectorizing trusted primitives** Array-based algorithms can be substantially accelerated inside TEE without TCB bloat. To squeeze performance, our key is to map their internal data parallelism to vector instructions of ARM [21]. Vectorization incurs low code complexity as the performance gain comes from a CPU feature that is already part of the TCB.

Our optimization focuses on Sort and Merge, two core primitives that typically dominate the execution of stream analytics. Inspired by vectorized sort and merge on x86 [26, 60], we build the ones for StreamBox-TZ with handwritten ARMv8 NEON vector instructions. Our sort outperforms the primitives that typically dominate the execution of stream analytics.

The challenges disqualify popular engine designs that organize stream events in hash tables (e.g., for grouping events by key) and rely on generic memory allocators [31, 64, 75, 82, 107]. The reasons are two: the hash table’s principle of trading space for time mismatches TEE’s limited memory; such generic allocators often feature sophisticated optimizations, adding tens of KSLoC to TCB [41, 56].

To address these challenges, we specialize TEE memory management for stream computations with two mechanisms: i) supporting unbounded buffers as the universal memory abstraction (§5.1); ii) placing memory by exploiting (untrusted) consumption plans and large virtual address space (§5.2).

### 5.1 Unbounded Array

We devise contiguous, virtually unbounded arrays called *uArrays* as the universal data containers used by computations in TEE. *uArrays* encapsulate all the data in a pipeline, including data flowing among trusted primitives as well as operator states traditionally kept in hash tables.

![The uArrays in one uGroup](Figure 5: The uArrays in one uGroup)

An *uArray* is an append-only buffer in a contiguous memory region for same-type data objects. Their lifecycles closely map to the producer/consumer pattern in streaming computations. One *uArray* can be in three states. **Open**: after an *uArray* is created, it dynamically grows as the producer primitive appends data objects to it. **Produced**: the data production completes and the end position of the *uArray* is finalized. **Retired**: the *uArray* is no longer needed and its memory is subject to reclamation. The memory allocator places and reclaims *uArrays* according to their states, as will be discussed in Section 5.2.

**Types** *uArrays* fall into different types depending on their scopes and enclosed data. A streaming *uArray* encapsulates data flowing from a producer primitive to a consumer primitive. A *state* *uArray* encapsulates operator state that outlives the lifespans of individual primitives. A temporary *uArray* live within a trusted primitive’s scope.

**Low abstraction overhead** An *uArray* spans a contiguous virtual memory region and grows transparently. The growth is backed by the data plane’s on-demand paging that completely happens in the TEE. For most of the time, growing an *uArray* only requires updating an integer index. Compared to manually managed buffers, this mechanism waives bounds checking of *uArray* in computation code and hence allows the compiler to generate more compact loops.

*uArrays* always grow in place. This contrasts to common sequence containers (e.g., C++ `std::vector` and Java `util.ArrayList`) that grow transparently but require expensive relocation. We will experimentally compare *uArray* with `std::vector` in Section 8.

### 5.2 Placing *uArrays* in *uGroups*

**Co-locating *uArrays*** The memory allocator co-locates multiple *uArrays* as a *uGroup* in order to reclaim them consecutively. Spanning a contiguous virtual memory region, a *uGroup* consists of multiple *produced* or *retired* *uArrays* and optionally an *open* *uArray* at its end, as shown in Figure 5. The grouping is purely physical: it is at the discretion of the allocator, orthogonal to stream computations, and therefore transparent to the trusted primitives and the control plane.

With the grouping, the allocator reclaims consumed *uArrays* by always starting from the beginning of an *uGroup*, as shown in Figure 5. To place a new *uArray*, the allocator decides whether to create a new *uGroup* for the *uArray*, or append the *uArray* to an existing *uGroup*. In doing so, the allocator seeks to i) ensure that each *uGroup* holds a sequence of *uArrays* to be
consumed consecutively in the future; ii) minimize the total number of live uGroups, in order to compact TEE memory layout and minimizes the cost in tracking uGroups. To this end, our key is to guide placement with the control plane’s data consumption plan, as will be presented below.

Consumption hints Upon invoking a trusted primitive $T$, the control plane may provide two optional hints concerning the future consumption order for the output of $T$:

- **Consumed-in-parallel ($\parallel_k$):** the control plane will schedule $k$ worker threads to consume a set of uArrays in parallel.
- **Consumed-after ($b_1 \leftarrow b_2$):** the control plane will schedule worker threads for consuming uArray $b_2$ after uArray $b_1$. The consumed-after relation is transitive. uArrays may form multiple consumed-after chains.

The control plane may specify these relations between new output uArrays (yet to be created) and existing uArrays.

**Hint-guided placement** The hints assist the data plane to generate compact memory layout and reclaim memory effectively. Upon allocating a uArray, the allocator examines the existing hints regarding to the uArray. ($\rightarrow$) prompts the allocator to place the uArrays on the same consumed-after chain consecutively in the same uGroup. Starting from the new uArray $b$ under question, the allocator tracks back on its consumed-after chain, and places $b$ after the first uArray that is both in state produced (i.e. its growth has finished) and located at the end of an uGroup. If no such uArray is available on the chain, the allocator creates a new uGroup for $b$.

($\parallel_k$) prompts the allocator to place uArrays $b_{1..k}$ in separate uGroups, so that delay in consuming any of the uArrays will not block the allocator from reclaiming the other uArrays. Our rationale is that despite $b_{1..k}$ are created at the same time, they are often consumed at different moments in the future: i) since StreamBox-TZ’s control plane threads independently fetch newly produced uArrays for processing as they become available (§3), the starting moments for processing $b_{1..k}$ may vary significantly, especially when the engine load is high; ii) even when $k$ worker threads start processing $b_{1..k}$ simultaneously, struggling workers are not uncommon, due to non-determinism of a modern multicore’s thread scheduling and memory hierarchy [24].

**Will misleading hints compromise security?** The control plane, being untrusted, may offer incorrect consumption hints. Yet, as hints only affect TEE memory placement policy, incorrect ones may lead to excessive TEE memory usage but do not compromise data security or TEE integrity, e.g. by introducing data races. Furthermore, incorrect hints will be detected by remote attestation (§6).

**Managing virtual addresses** All uGroups grow in place within one virtual address space. To avoid collision and expensive relocation, the allocator places them far apart by leveraging the large virtual address space dedicated to a TrustZone TEE. The space is 256TB on ARMv8, 10,000×

| Field | Description | Length |
|-------|-------------|--------|
| Ts    | Data plane timestamp | 32 bits |
| Op    | Primitive type, including ingress/egress | 16 bits |
| WinNo | Monotonic window sequence number | 16 bits |
| Data  | An uArray ID or a watermark value | 32 bits |
| Hint  | An optional consumption hint | 64 bits |
| Count | Number of data/hint fields that follow | 16 bits |

![Figure 6: Audit records: their fields (top) and the uncompressed physical layout (bottom)](image)

larger than the total physical DRAM which is often several GBs. Hence, the allocator simply reserves for each uGroup a virtual address range as large as the total TEE DRAM. We will validate this choice in Section 6.

### 6. Attestation for Correctness and Freshness

StreamBox-TZ collects evidences for cloud consumers to verify two properties: correctness, i.e. all ingested data is processed according to the stream pipeline declaration; freshness, i.e. the pipeline has low output delays.

The above objective has several notable aspects. i) We verify the behaviors of untrusted control plane, i.e., which primitives it invokes on what data and at what time. We do not verify trusted primitives, e.g. if a Sort primitive indeed produces ordered data. ii) Verifying data lineages at the control plane may specify these relations between new output uArrays (yet to be created) and existing uArrays. iii) The windows of stream computations and watermarks triggering the computations must be attested, which are key to stream model (§3). iv) As the volume of evidences can be substantial and even dwarf the size of analytics results, evidences must be compacted to save uplink bandwidth [77, 101].

Therefore, StreamBox-TZ provides the following verification mechanism. Agnostic to the pipeline being executed, the data plane monitors dataflows among primitive instances at the TEE boundary. Based on its observation, the data plane generates audit records. For low overhead, it eschews building data lineages on-the-fly unlike much prior work [48, 49, 89]. The data plane compreses audit records and flushes to the cloud both periodically and upon externalizing any analytics result. We describe details below.

**Audit records** As being invoked by the control plane, the data plane generates audit records. As illustrated in Figure [9] the records track i) ingested and externalized uArrays, ii) associations between uArrays and windows, and iii) primitive executions (with optional hints supplied by the control plane) which establish derived-from relations among uArrays. The records further include ingested watermark values and watermarks that trigger computations, which are crucial
for determining output delays as will be discussed below. The data plane timestamps all the records, allowing attestation for execution timing. It generates monotonically increasing identifiers for recorded uArrays.

**Attesting analytics correctness** The cloud verifier checks if all ingested uArrays flow through the expected trusted primitives. Such dataflows are deterministic given the arrivals of input data (including their windows), the watermarks, and the pipeline declaration. Hence, the verifier replays all ingestion records on its local copy of the same pipeline. It checks if all the records resulting from the replay match the ones reported by the edge (except timestamps). The replay is symbolic without actual computations and hence fast.

**Attesting result freshness** The key for the verifier to calculate the delay of an output result $R$ is to identify the watermark that triggers the externalization of $R$, according to the delay definition in Section 2.2. From the ingress record of $R$, the verifier traces backward following the derived-from chain(s) until it reaches an execution record indicating that a watermark $W$ triggers the execution. The verifier looks up the ingress record of $W$. It calculates the difference between $W$’s ingress time and $R$’s egress time to be the delay of $R$.

### Example

In Listing 1, an uArray with identifier 0xF0 is ingested and segmented into two uArrays (0xF1 and 0xF2) for window 0 and 1 respectively. Sort consumes uArray 0xF1 and produces uArray 0xF3. A watermark with value 100 arrives and completes window 0. Triggered by the watermark, SUM consumes uArray 0xF3 of window 0 and produces uArray 0xF5 as the result of window 0.

The cloud verifier replays the ingress records on its local pipeline copy and learns that uArray 0xF1 is processed adhering to the pipeline declaration while uArray 0xF2 is yet to be processed. It will assert analytics incorrectness if 0xF2 remains unprocessed until a future watermark completes window 1 (not shown). To verify result freshness, the verifier traces result 0xF5 backward to find its trigger watermark 0xF4 and calculates the output delay to be 15 (30 − 15).

### Columnar compression of records

The data plane compresses audit records by exploiting rich locality within one record field and known data distribution in each field. As shown in Figure 7, the data plane produces raw audit records in memory in row format (i.e. one record after the other). Before uploading a sequence of records, it compresses them by separating the record fields (i.e. columns) and applies different encoding schemes to compress individual columns: i) Huffman encoding for primitive types (Op) and data counts (Cnt), the two columns likely contain skewed values; ii) delta encoding for timestamps (Ts), uArray identifiers (Data), and window numbers, which increment monotonically. Our compression is inspired by columnar databases [96]. We will evaluate the efficacy of compression in Section 8.

### 7. Implementation

We build StreamBox-TZ for ARMv8. StreamBox-TZ reuses most control functions of StreamBox [75], an open-source research stream engine for x86 servers. Yet, as StreamBox mismatches a TEE (§3.1), StreamBox-TZ contributes a new architecture and a new data plane. StreamBox-TZ communicates with source sensors and cloud consumers over ZeroMQ TCP transport [54] which is known for good performance. The new implementation of StreamBox-TZ includes 12.4K SLoC.

#### TEE choice

We built StreamBox-TZ’s data plane atop OP-TEE [63] (v2.3), a popular TEE kernel for TrustZone. In the TEE, the StreamBox-TZ code runs on the least privileged level (EL0), isolated from the TEE kernel on EL1. StreamBox-TZ relies on OP-TEE for secure key storage. We modify OP-TEE’s exception handling to implement on-demand paging.

#### Input batch size

A key parameter of StreamBox-TZ, trades off between delays in executing individual primitives, the rate of TEE entry/exit, and attestation cost. We empirically determine it as 100K events and will evaluate its impact (§8).

#### Opaque references

The data plane generates 64-bit random integers as opaque references for uArrays. It keeps the mappings from references to the uArray addresses in a table. The data plane validates incoming opaque references by table lookup and only accepts ones that exist in the table. The table incurs minor overhead, as live opaque references are often no more than a few thousands.

### 8. Evaluation

We answer the following questions through evaluation:

- Does StreamBox-TZ mitigate in-scope attacks? (§8.1)
- What is StreamBox-TZ’s performance and how is it compared to other engines? What is the overhead? (§8.2)
- How do our key designs impact performance? How effective is audit record compression? (§8.3)

#### 8.1 Security Evaluation & Analysis

**TCB size** Table 3 shows a breakdown of the StreamBox-TZ source code. Despite a sophisticated control plane, the
StreamBox-TZ's memory management is in 740 SLoC, 9 data plane only adds 5K SLoC to the TCB. In particular, parentheses which 5K SLoC are in TCB. Binary code sizes shown in Table 3: A breakdown of the StreamBox-TZ source, of the data plane.

### Analysis of unmitigated attacks

The following out-of-scope attacks (§2.4) are unmitigated. i) Exploitation of TEE kernel bugs. Although designed for security, TEE kernels still have bugs that may be exploited [6,7,53]. StreamBox-TZ does not strengthen TEE kernel security. ii) Side channel attacks. Adversaries out of TEE may still learn properties (e.g. data skew) of TEE-protected data by observing hardware usage such as memory access pattern [67]. iii) Physical attacks, e.g. sniffing TEE’s DRAM access [18, 28]. Note that many of these attacks are mitigated by prior work [39].

### 8.2 Performance & Overhead

#### Methodology

We evaluate StreamBox-TZ on a HiKey board as summarized in Table 2. We chose HiKey for its good OP-TEE support [65] and that it is among the few boards with TrustZone programmable by third parties. We built Generator, a program sends data streams over ZeroMQ TCP transport [54] to StreamBox-TZ. We run the cloud consumer on an x86 machine. Data streams are encrypted with 128-bit AES.

In the face of HiKey’s platform limitations, we set up the engine ingestion as follows. i) Although Gigabit Ethernet on edge platforms is common [8, 9], Hikey’s Ethernet interface (over USB) only has 20MB/sec bandwidth. We have verified that the interface is saturated by StreamBox-TZ with more than 4 cores. Hence, we report performance when StreamBox-TZ and Generator both run on HiKey communicating over ZeroMQ TCP [54] to StreamBox-TZ. We run the cloud consumer on an x86 machine. Data streams are encrypted with 128-bit AES.

As summarized in Table 4, we test StreamBox-TZ as well as three modified versions: EF ClearIngress ingests data in cleartext; this is allowed if source-edge links are trusted as defined in our threat model (§2.4). EF IOviaOS does not exploit TrustZone’s secure IO: the untrusted OS ingested (encrypted) data and copies the data across TEE boundary to the data plane. Insecure completely runs in the normal world with ingress and egress in cleartext, showing native performance. This is basically StreamBox-TZ without the Secure IO interface.

#### 8.2.1 Ingress benchmarks

We report the engine performance as its maximum input throughput when the pipeline output delay (defined in §2.2) remains under a target set by us.

### Benchmarks

We use the following six benchmarks. We use fixed windows, each of which encompasses 1M events and spans 1 second of event time. Each event consists of 3 fields (12 Bytes) unless stated otherwise. (1) Top Values Per Key (TopK) groups events based on keys and identifies the K largest values in each group in each window. (2) Counting Unique Taxis (Distinct) identifies unique taxi IDs and counts
them per window. For input events we use a dataset of taxi trip information containing 11 K distinct taxi IDs [59]. (3) Temporal Join (Join) joins events that have the same keys and fall into same windows from two input streams. (4) Windowed Aggregation (WinSum) aggregates input values within each window. We use the Intel Lab Data [70] consisting of real sensor values as input. (5) Filtering (Filter) filters out input data, of which field falls into a given range in each window. We set the selectivity as 1% as done in prior work [63]. (6) Power Grid (Power), derived from a public challenge [58], finds out houses with most high-power plugs. Ingesting a stream of per-plug power samples, it calculates the average power of each plug in a window and the average power over all plugs in all houses in the window. Then, for each house, it counts the number of plugs that have higher load than average. Finally, it emits the houses that have most high-power plugs in the window. The event for this benchmark is composed of 4 fields (16 Bytes).

Benchmark 2, 4, and 6 use real-world datasets; others use synthetic data sets of which fields are 32-bit random integers. Note that StreamBox-TZ’s GroupBy operator based on sort and merge are insensitive to key skewness [15].

End-to-end performance Figure 8 shows the throughputs of all benchmarks as a function of hardware parallelism. StreamBox-TZ can process to multiple millions of events per second, while keeping sub-second output delays. For simpler pipelines such as WinSum and Filter, StreamBox-TZ processes around 12M events/sec (140 MB/sec). This throughput saturates one GbE link which is common on IoT gateways [8 9]. Overall, StreamBox-TZ can use all 8 cores in a scalable manner.

Comparison to existing stream engines We qualitatively compare StreamBox-TZ with SecureStreams [51], the only stream engine with strong data security to our knowledge. SecureStreams uses SGX to protect stream operators in a distributed environment. On a benchmark similar to WinSum it was reported to achieve 10 MB/sec, one magnitude lower than StreamBox-TZ on WinSum. SecureStreams achieved such performance on a small x86 cluster which has much richer resource than HiKey: the former has faster CPUs (8x i7-6700@3.4GHz versus 8x Cortex-A53@1.2GHz), larger DRAM (16 GB versus 2 GB), higher power (130W versus 36W), and higher cost ($600 versus $65).

We further experimentally demonstrate StreamBox-TZ outperforms popular stream engines [19 44 82] (we will contrast StreamBox-TZ to StreamBox [75] as security overhead below). As shown in Figure 9 on the same hardware (HiKey) and the same benchmark (WinSum), StreamBox-TZ achieves at least 10× higher throughput than others. Note that these commodity engines have no security mechanisms. One could create secure variants of these engines by additionally applying generic TEE frameworks [66]; with the additional overhead, such secure variants will exhibit even lower performance.

In summary, on an edge platform StreamBox-TZ outperforms a recent secure engine and popular insecure en-

Table 4: Engine versions for comparison (plots in Figure 8)

| Legend & Version | Data Plane | In/Egress Path | Ingress Data | Egress Data |
|------------------|------------|----------------|--------------|-------------|
| StreamBox-TZ     | in TEE     | Sec IO         | Encrypted    | Encrypted   |
| ST Clearingress  | in TEE     | Sec IO         | ClearTxt     | Encrypted   |
| ST IO via OS     | in TEE     | via OS         | Encrypted    | ClearTxt    |
| Insecure         | out TEE    | in OS          | ClearTxt     | ClearTxt    |

* Through TrustZone Secure IO directly to TEE
♯ Equivalent to a StreamBox invoking optimized stream compute

Figure 8 shows the throughputs (lines, left/right y-axes) as a function of CPU cores (x-axis) under given output delays (above each plot). Steady consumptions of TEE memory as columns with annotated values. See Table 4 for legends and explanations.
The throughput of StreamBox-TZ is much higher than commodity insecure engines [19, 44, 82] on HiKey. Benchmark: windowed aggregation; target output delay: 50ms. StreamBox-TZ benefits from i) data parallelism exploited in its optimized data plane; ii) task parallelism created by its control plane and supported by the coherent address space in its data plane. The last enables trusted primitives to exchange data via shared memory, instead of using encrypted message-passing as the distributed workers of SecureStreams must do.

Security overhead We investigate the overhead of the new security mechanism contributed by StreamBox-TZ – its isolated data plane. We assess the overhead as the throughput loss of EF ClearIngress as compared to Insecure (i.e., native performance as StreamBox [75] invoking StreamBox-TZ’s stream computations), both paying same costs for data ingress. The security overhead is less than 25% in all benchmarks. This overhead is similar to or lower than recent TEE systems [22, 33, 60], of which overhead ranges from 20%–70%. Our overhead is slightly higher than VC3 (~20%) measured on emulated SGX [89].

To quantitatively understand the constituents of the overhead, we profile the execution of GroupBy, one of the most costly operators. In particular, we test different input batch sizes that have strong impact on TEE entry/exit rates and hence isolation overhead [83]. Figure 10 shows a run time breakdown. When each input batch contains 128K (close to the value we set for StreamBox-TZ) or more events, more than 90% of the CPU time is spent on actual computations in TEE. The CPU usage of TEE memory management is as low as 1–2%. In the extreme case where each input batch contains as few as 8K events, the overhead of world switch starts to dominate. Most of the world switch overhead comes from OP-TEE instead of the CPU hardware (a few thousand cycles per switch), suggesting room for OP-TEE optimization.

Impact of decrypting ingress data Decrypting ingress data is needed if source-edge links are untrusted [2, 4] and source must send encrypted data. It has substantial performance impact. By comparing StreamBox-TZ to EF ClearIngress, turning on/off ingress decryption leads to 4%–35% throughput difference when all 8 cores are in use. The performance gap is more pronounced for simple pipelines, which has higher ingestion throughput leading to higher decryption cost.

TEE memory consumption While sustaining high throughput, StreamBox-TZ consumes a moderate amount of physical memory, ranging from 20 MB to 130 MB as shown in Figure 11. The memory consumption is as low as 1–6% of the total system DRAM. The virtual memory usage is also low, often 1–5% of the entire virtual address space in OP-TEE. The memory consumption increases as the throughput scales up, since there will be more in-flight streaming data.

Attestation overhead Attestation incurs minor overhead to both the edge and the cloud. We measured that StreamBox-TZ produces 300–400 audit records per second across all our benchmarks, and spends a few hundred cycles on producing each record. Compressing such record streams on HiKey consumes 0.2% of total CPU time. Our consumer written in Python on a 4-core i7-4790 machine replays 57K records per second with a single core, suggesting a capability of attesting near 500 StreamBox-TZ instances simultaneously. We will evaluate the efficacy of record compression in Section 8.3.

8.3 Validation of Key Design Features

Exploitation of secure IO As shown in Figure 8, a comparison between StreamBox-TZ and EF IOViaOS demonstrates the advantage of directly ingesting data into TEE and bypassing the OS: StreamBox-TZ outperforms the latter by up to 20% in throughput due to reduction in moving ingested data.

Trusted primitive vectorization Our optimizations with ARM vector instructions are crucial. To show this, we examine GroupBy, one of the top hotspot operators. When we replace the vectorized Sort that underpins GroupBy with two popular implementations (qsort() from the the OP-TEE’s libc and std::sort() from the standard C++ library), we measured the throughput of GroupBy drops by up to 7× and 2×, respectively. We have similar observation on other operators.

uArray on-demand growth The on-demand growth of uArrays incurs low overhead. To show this, we compare it to std::vector, a widely used C++ sequence container with on-demand growth. We test uArray and std::vector with a
A large TCB. VC3 [89] and SecureStreams [51] use SGX by isolating computations in an OS process, resulting in Secure data analytics. DARKLY [57] protects sensor data by isolating computations in an OS process, resulting in a large TCB. VC3 [89] and SecureStreams [51] use SGX to protect the operators in distributed analytics. They lack optimizations for parallel execution in one TEE on the edge. To process data confidentiality, STYX [95] computes over encrypted data, a method likely prohibitively expensive to edge platforms. Opaque [109] protects data access patterns of distributed operators, targeting a threat out of our scope. Many systems support attestation of TEE integrity [61]. Data provenance [48, 93] provides full history of output data. To verify analytics correctness, VC3 [89] propagates work summaries among mappers/reducers; Opaque [109] has each computation task check its input data lineage. Lacking notions of stream watermarks and windows, these methods are insufficient to verify whether all ingested data is processed according to the stream model and pipeline. Furthermore, unlike Opaque, StreamBox-TZ’s TEE remains agnostic to the executed pipeline for simplicity.

**TCB minimization** Minimizing TCB is a proven approach towards a trustworthy system. Flicker [73] directly executes security-sensitive code on baremetal hardware. Trustvisor [72] shrinks its TCB to a specialized hypervisor. Sharing a similar goal, StreamBox-TZ addresses unique challenges in supporting data-intensive computation on a minimal TCB.

**Trusted Execution Environments** Much work isolates security-sensitive software components. Terra [46] supports isolation with a virtual machine monitor. Many systems used TrustZone and SGX [74] for TEE. Some of them enclose TEE in whole applications [22, 27, 53, 49], while others partition existing programs for TEE [66, 84, 91]. These approaches often result in larger TCBs and/or higher overhead than StreamBox-TZ and are thus less desirable for edge stream analytics. TEE components are designed for specific uses, including protecting mobile app classes [86], enforcing security policies [50], remote attestation of application control flows [13], and controlling data access [34]. None addresses data-intensive computation as StreamBox-TZ does.

**Edge processing** is evolving from a vision [88, 90] to a practice [37, 42, 76]. Most recent research focused on programming paradigms [55], developing and deploying novel application [29, 50, 101], and distributed resource management [79]. Complementary to them, StreamBox-TZ focuses on secure analytics on the edge.

**Stream processing systems**, in response to big data challenges, evolve from single-threaded [12, 32, 40, 71, 94, 98] to massively parallel systems [14, 64, 78, 83, 83, 100, 107]. The existing systems, despite inspiring, often focus on scalability challenges, such as fault tolerance [107], fast reconfiguration [102], multicore parallelism [31, 75], and use of GPUs [63]. Targeting high bandwidth memory (HBM), an anonymous paper [11] presents a stream engine contributing compressed key-pointer arrays, operators optimized with Intel AVX-512 to exploit memory bandwidth, and HBM management. Few systems achieve strong data security and performance simultaneously as StreamBox-TZ does.

Figure 12: On-demand growth of uArrays vs. std::vector

Figure 13: Compression of audit records saves uplink bandwidth substantially.

**Hint-guided memory placement** (§2) To demonstrate the efficacy of consumption hints, we compare our allocator to the following generation-based version: the modified allocator acts based on the heuristics that all the uArrays produced by the same primitive belong to the same generation and are likely to be reclaimed altogether. Accordingly, the modified allocator places these uArrays in the same uGroup. Once these uArrays are all consumed, the memory for the whole uGroup is reclaimed. As shown in Figure 11 in three benchmarks, the modified allocator incurs up to 35% increase in physical memory consumption. This is because without hints, it cannot place uArrays based on future consumption order as StreamBox-TZ does.

**Compression of audit records** (§6) The compression significantly saves the uplink bandwidth. We test two benchmarks (WinSum and Power) on two extremes of the spectrum of computation cost, and test two very different input batch sizes. This is because simpler computations and smaller batch sizes generate audit records at higher rates.

Figure 13 shows that StreamBox-TZ compresses audit records by 5×–6.7×. In an offline test using gzip to compress the same records, we find our compression ratios are 1.9× higher than gzip. The compression saves 2–40 KB/sec of uplink bandwidth. Such savings are significant compared to the uploaded analytics results, which are 144 bytes/sec for WinSum and 400 bytes/sec for Power on average.

**9. Related Work**

**Secure data analytics** DARKLY [57] protects sensor data by isolating computations in an OS process, resulting in a large TCB. VC3 [89] and SecureStreams [51] use SGX to protect the operators in distributed analytics. They lack optimizations for parallel execution in one TEE on the edge.
10. Conclusions

This paper presents StreamBox-TZ, a secure stream analytics engine designed and optimized for a TEE on an edge platform. StreamBox-TZ offers strong data security, verifiable results, and compelling performance. On an octa core ARM machine, StreamBox-TZ processes up to tens of millions of events per second; its security mechanisms incur less than 25% overhead.

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