A Fast Lightweight Time-Series Store for IoT Data

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ABSTRACT

With the advent of the Internet-of-Things (IoT), handling large volumes of time-series data has become a growing concern. Data, generated from millions of Internet-connected sensors, will drive new IoT applications and services. A key requirement is the ability to aggregate, preprocess, index, store and analyze data with minimal latency so that time-to-insight can be reduced. In the future, we expect real-time data collection and analysis to be performed both on small devices (e.g., in hubs and appliances) as well in server-based infrastructure. The ability to localize sensitive data to the home, and thus preserve privacy, is a key driver for small-device deployment.

In this paper, we present an efficient architecture for time-series data management that provides a high data ingestion rate, while still being sufficiently lightweight that it can be deployed in embedded environments or small virtual machines. Our solution strives to minimize overhead and explores what can be done without complex indexing schemes that typically, for performance reasons, must be held in main memory. We combine a simple in-memory hierarchical index, log-structured store and in-flight sort, with a high-performance data pipeline architecture that is optimized for multicore platforms. We show that our solution is able to handle streaming insertions at over 4 million records per second (on a single x86 server) while still retaining SQL query performance better than or comparable to existing RDBMS.

1. INTRODUCTION

By 2020, analysts predict that there will be over 25 billion connected devices in the Internet-of-Things (IoT). Together, these devices will generate unprecedented volumes of data that must, in order to create value, be efficiently indexed, stored, queried and analyzed. A single aspect that ties all of this data together is that it is time-series. Time is either evident as an explicit dimension in the data (e.g., a sensor generated time-stamp) or implicit by the time at which a data sample reaches an aggregation node (e.g., a hub or server).

Existing databases and storage systems predominantly handle time-series data no differently from other data. There does exist a notion of time-series database, some that are based on RDBMS and some that based on NoSQL type architectures. While APIs and data types may be provided specifically for time, the underlying storage and indexing mechanisms are no different. As a consequence of generality, existing RDBMS solutions are typically limited to ingress streams of 200-300K RPS on a single commodity server and 25-30K RPS on an embedded platform. Their performance is limited primarily because of the complexity introduced by indexing with B+-trees [14] or LSM trees [18] as well as the maintenance of locks and state for transactional processing.

However, a key strength of RDBMS solutions is their ability to support advanced queries through SQL support [15]. SQL provides a powerful language for performing arbitrary queries that require filtering (selection), manipulation (e.g., data conversion), projection (e.g., aggregation), and joins. SQL also provides a standardized and industry accepted interface to which analytic solutions (e.g., Apache Spark [20], Tableau [9], SAS [8], SAP [7]) and applications can be easily integrated.

We believe that this type of complex query is a key enabler for future IoT applications that derive value by creating insight from data. By digitally enabling a product through sensor augmentation, massive volumes of data can be collected about operation, wearing and environmental conditions. Combining this with analytics that can quickly slice-and-dice the data, enables new hybrid product-service models to be realized (e.g., preventative maintenance, energy optimization).

While most database solutions provide SQL access to data, they inherently cannot support continuous ingest of large-volumes of streaming data. Those solutions that do provide higher ingest rate capabilities typically make extensive use of main memory to hold indexing information.

The focus of this work is the development of a lightweight and memory-efficient architecture that supports an order-of-magnitude higher ingest rate over existing RDBMS and time-series database solutions. We do this while still providing both the flexibility and power of SQL, and a minimal run-time memory overhead so as to be suitable for deployment in embedded or resource-limited environments.

Our solution, herein termed Lightweight Time-Series Store (LTSS), is domain-specific in that it is designed to leverage the characteristics of time-series data in an IoT application.
context.
Specifically, LTSS is designed with the following assumptions in mind:

i. Data is highly-ordered - Time advances and thus data is inherently in order. Network routing and imprecise clock synchronization (i.e., inability to have a true global clock) can cause out-of-order data, but this is typically limited to a finite time window (samples outside of such a window can be considered invalid and not useful).

ii. Data is immutable - Each data element represents a sample in time that may or may not be subsumed by a subsequent sample, but in itself represents an unchangeable history. Applications generally summarize and aggregate data to create useful insight.

iii. Both epoch and calendar-based reasoning are necessary for analytics - While epoch-based time are useful, alone they are insufficient. Many analyses require reasoning in terms of human-understandable concepts (e.g., hours, days, months). For example, queries such as “Is the current value the highest for the month?” are typical.

iv. Data can be lost - Most data is collected over unreliable wireless network links and through congested IP routers. Sensor-based data sources do not, in the most part, have the ability to perform re-transmission due to limited energy and memory capacities. IoT applications are predominantly resilient to data loss.

1.1 Deployment Requirements

Our architecture focuses on indexing and query at the ingestion node. The ingestion node is the first “point of contact” for data being collected from sensors distributed across a network. Data is received either directly from the sensor (e.g., where a sensor has direct Internet connectivity) or from a hub (e.g., that aggregates across multiple non-IP sensors). Its role is to receive streaming data, which is then preprocessed, stored and indexed according to one or more time fields, and made accessible through read-only query interfaces.

The ingestion node is responsible for the management of “fresh” data. It has limited storage resources and can only store data for a given period of time. Old data is either off-loaded to cold-storage (e.g., in the cloud) or erased.

An ingestion node implementation may take multiple forms depending on the deployment context. For example, in the home it may be realized in one or more hub devices or embedded into existing consumer electronics (e.g., a SmartTV). At the network edge, the ingestion node may be deployed on commodity x86 servers or cloud infrastructure. We do not envisage the deployment of ingestion nodes at the cloud back-end due to the cost of back-hauling data.

For our work we are particularly focused on in-home and edge deployments. We define the following requirements accordingly:

i. High-Volume Data Rates - Support for continuous aggregation and summarization of large volumes of streaming data resulting from an increasing number of deployed sensors with higher data generation rates (i.e., increased sampling frequencies).

ii. Flexible Memory Model - Tailorability of main memory overhead according to available resources. Less than 32MB minimum memory footprint in an embedded environment.

iii. Low-Latency for Real-time Applications - Freshness of data (i.e., the time between the data being received and it being accessible to queries) should be in the order of 200-400ms (latency deemed necessary for interactive applications).

iv. SQL-based Query Interface - The system should support SQL in order to easily integrate with existing platforms and applications while also providing query flexibility to support complex operations and joins across multiple data sources.

v. Data Aging and Resource Re-cycling - Data should be stored using a fixed set of resources (disk, memory). Aging data should override new data as resources are exhausted.

1.2 Outline

The rest of this paper is organized as follows. Section 2 presents some background and related work, and positions our own work in the field of time-series/streaming databases. In Section 3, we present our architecture and provide details on how data from continuous streams is ordered, indexed and stored, and how it is integrated with an SQL front-end. Section 4 describes details around the prototype implementation. Next, Section 5, presents our evaluation based on three real-world data sets with representative queries and also discuss our testing methodology. Finally, in Section 6 we offer our conclusions.

2. RELATED WORK

There currently exists a broad range of time-series databases, both commercially and as open source. These databases provide additional capabilities that are specific to streaming data ingest and time-oriented queries. With the advent of IoT, these databases vendors and developers are touting support for store and analysis of large volumes of sensor data. The specific features of each are also varied. Table 1 lists some of the more popular time-series database solutions and highlights their different feature sets.

The work in this paper focuses on the following key capabilities:

- High ingest rates
- Support for an SQL interface
- Local write-append data storage

Of the technologies listed in Table 1, PipelineDB, ParStream, IBM Informix and InfiniFlux meet this criteria and are thus most relevant to our work. However, they are not designed with embedded and other resource constrained environments in mind.

Pipeline DB [2], an open source project primarily developed by Usman Masood, is aimed at performing SQL queries on streaming data. Specifically, it is designed to excel at SQL queries that reduce the cardinality of streaming data sets through aggregation and summarization. Raw data is discarded once it has been read by the continuous queries.
| Name          | Impl. Lang. | Interface   | SQL Ad-hoc Queries | Cont. Queries | License     | Data Store | Data Struct. | Advertised Ingest Rate (Per-Node) |
|--------------|------------|-------------|--------------------|--------------|-------------|------------|--------------|----------------------------------|
| Akumuli      | C++        | JSON        | N                  | N            | Open        | Local      | Log          | 200K RPS                         |
| Bolt         | C#         | C# API      | N                  | N            | Proprietary | Distributed | LSM          | 100K RPS                         |
| Druid        | Java       | HTTP/REST   | N                  | Y            | Distributed | Columnar   | 10K RPS      |                                  |
| IBM Informix | Java       | HTTP/REST/SQL/JSON | Y | N | Commercial | Local   | unknown | 420K RPS |
| InfiniDB     | C++        | SQL         | Y                  | Y            | Commercial | Local      | Columnar    | 2M RPS                           |
| InfluxDB     | Java       | HTTP/REST   | Partial            | Y            | Open       | Local      | LSM          | 100-150K RPS                     |
| OpenTSDB     | Java       | HTTP/CLI    | N                  | N            | Open       | Distributed | HBase/Cassandra | 100K RPS |
| ParStream    | C++        | JDBC/SQL    | Y                  | N            | Commercial | Distributed | Columnar    | 500K RPS                         |
| PipelineDB   | C++        | SQL         | Y                  | Y            | Open       | Local      | B-tree       | 500K RPS                         |
| Prometheus   | Go         | HTTP/JSON   | Y                  | N            | Open       | Local      | LSM          | unknown                         |
| LTSS         | C++        | SQL         | Partial            | Y            | Proprietary| Local      | Log          | 4M+ RPS                          |

Table 1: Popular Time-Series Databases.

that need to read it. Pipeline DB provides full SQL support and provides additional constructs to support queries on sliding windows and continuous materialization. As with our own philosophy, Pipeline DB aims to eliminate an explicit extract-transform-load stage from the data analytics pipeline. The system is based on, and fully compatible with, PostgreSQL 9.4, and therefore uses B-tree/hash based indexing. Pipeline DB uses PostgreSQL’s `INSERT` and `COPY` constructs for writing data. In the long term, the Pipeline DB team hopes to factor out the solution as a PostgreSQL extension, suggesting that they do not plan to change the storage internals.

ParStream [4, 10], recently acquired by Cisco, is a broader analytics platform aimed at IoT (originally ParStream was touted as a real-time database for big data analytics). Their key differentiators are fast ingest, edge analytics, and the ability to create real-time insights through concurrent fast queries. The ParStream architecture leverages both in-memory processing (for indices and data caching) and disk-based storage. The system has been explicitly designed to exploit multicore architectures by the use of parallel processing. The crux of the ParStream DB indexing is their High Performance Compressed Index (HPCI), which is currently in patent application [10]. HPCI is a compressed bitmap index on which queries can be directly executed. This both reduces the time to scan records and the memory footprint for the index. Unlike LTSS, the ParStream architecture separates out Import and Query Nodes. This allows them to alter the ratio of query and ingest resources. Import Nodes, basically perform an extract-transform-load stage, convert incoming data into an internal data partition format. It is possible to transform data based on SQL statements executed in the Import Nodes. ParStream provides SQL over JDBC/OBDC, as well as a C++ interface. The system also supports cluster-based deployment and replication, which LTSS does not.

InfiniFlux [3] is another commercial time-series database solution. It is a columnar DBMS tailored to processing time-series “machine data” at high ingest speeds (millions of records per second on a single node). Like ParStream, InfiniFlux uses an in-memory bitmap based index to manage the data. Columns are set up for each potential value and bit vectors used to indicate the value for a given row. This provides significant compression for data sources whose value ranges are limited (e.g., sensor data ranging for 0-255). InfiniFlux is designed to achieve maximum analytical performance by storing records in a hybrid arrangement of column-oriented coupled with time-partitioned. InfiniFlux advertises an ingest rate of around 2M records per second.

Finally, IBM Informix, a broader commercial RDBMS suite, provides a specific solution for time series data known as Informix TimeSeries [2]. At the core of ITS is the DataBlade extensibility framework, which allows the user to customize and enhance types and functions in the database system. In essence, the TimeSeries enhancements provide additional data types and compressed storage schemes. Similar to the LTSS composite time type (see Section 3.1), Informix TimeSeries provides a `CalendarPattern` data type that allows intervals based on calendar fields (e.g., second, minute, hour) to be easily defined. It also provides other time-specific data types for regular and irregular time-series (grouping together rows ordered by time stamp). Time-series data can be stored in rows (when less than 1500 bytes) or in `containers` that store the data outside of the database tables. These, like LTSS, are contiguous append-only logs.

All of these solutions are primarily designed with server deployment in mind. They intentionally leverage a combination of storage and (large) main memory to accelerate system performance. LTSS on the other hand, makes minimal use of main memory, but is designed to exploit random access performance of new non-volatile RAM storage technologies.

### 3. ARCHITECTURE

The LTSS system is designed around a component-based data processing architecture that allows flexible configuration of real-time compute and storage.

![LTSS Integration](image)

Figure 1: LTSS High-Level View.

The LTSS ingestion pipeline has four main components (see Figure 1):
• **Channel Source** - The Channel Source component has an active thread that consumes data from the NIC actor (via a data plane channel). It simply takes each record and passes it on through a down-stream call.

• **Time Conversion** - Conventional UNIX epoch (or higher precision) time stamps are converted to a concise calendar based “composite” time (see Section 3.1). This allows the system to accelerate data selection based on calendar patterns (e.g., every first Tuesday in the month). Note that this conversion is performed during the data ingest.

• **Time Ordering** - The Time Ordering component ensures that ingress packets are ordered according to time. Out of order records may arise from lack of global clock synchronization, Internet routing, and OS scheduling. Records are ordered through an insertion sort.

• **Record Store** - The final stage of the ingestion pipeline is the Record Store. The Record Store provides an interface for write-append, time-ordered storage of records. Data is stored as a log with in-memory metadata to accelerate look up. We do not currently do any compression on the stored data.

The query side (read-only) runs as a separate process that interacts with the pipeline through shared memory.

### 3.1 Composite Time Representation

A calendar-based, composite time type (ct ime_t), with microsecond precision, is used to represent indexed time columns (this sub-second precision is necessary for IoT applications). The ctime_t type uses a compact bit field representation totaling only 8 bytes (see below). This is considerably more memory efficient than the POSIX tm structure that requires 36 bytes. Calendar-based field extraction is more efficient with composite time than using a basic time stamp.

```c
unsigned usec: 20; // range 0-999999
unsigned sec: 6; // 0-59
unsigned min: 6; // 0-59
unsigned hour: 5; // 0-23
unsigned wday: 3; // 0-6
unsigned day: 5; // 0-31
unsigned month: 4; // 0-11
unsigned year: 5; // 2000 up to 2031
unsigned timezone: 5; // 0-23
unsigned pm: 1; // 0-1
unsigned reserved: 3;
```

All time columns, on which query constraints can be expressed, are represented with the ctime_t type. Standard converters, that are executed in the pipeline, are implemented for epoch and ISO 8601 string-based time formats. Records stored in the LTSS must have at least one composite time field. The current implementation only supports constraints on one instance of composite time.

### 3.2 In-flight Record Ordering

Ingress records are allocated to “quantum buckets” (see Figure 3). Each bucket represents a relative time window. The target bucket for a given record is simply calculated by rounding down the record’s time stamp (epoch or composite). Buckets are created on-demand providing that no future bucket (i.e., with a greater time stamp) has already been created and closed (a record attempting to create such a bucket is considered “delinquent” and is dropped). Buckets are arranged in an ordered queue and expired from the tail according to time. The duration of the quantum, and thus the length of the wait in the queue before sorting and closing, implicitly defines the freshness of data. This attribute is configurable.

When the Time Ordering component expires a bucket, it asynchronously passes the set of records for the quantum to a sorting thread. This performs an insertion sort on the records before passing them to the Record Store. We use an insertion sort because of its good performance in sorting nearly ordered lists with typically a small number of places an element can be out of order.

### 3.3 In-Memory Directory Index

The Record Store uses a shared memory directory-style index to accelerate look up performance. A dynamic list of absolute byte offsets is maintained for each composite time field down to second granularity (see Figure 3). Each list maintains offsets to the starting point for every instance of the given field. For example, the Year list contains a single offset for each year the data covers. The Month list contains an offset for each month covered and so on and so forth. Interval trees are used to augment the field lists so that the location of the appropriate offset can be quickly made. This is especially beneficial for least-significant fields such as minutes and seconds.

Query constraints are applied starting from the most-significant field (e.g., Year = 2015). Once the offset is located for the appropriate year (more than one year may exist), it is used to quickly narrow on the next constraint (e.g., Month = Mar). That is, the offset for the matching 2015 year is subsequently used in matching on the interval tree to find the first matching month within 2015 (see Figure 3). Sub-second constraints are realized through an exponential search (i.e., binary chop).

A persistent version of the in-memory metadata is maintained for fast recovery. The memory footprint for this index is typically in the order of tens of megabytes.

![Figure 2: Time Ordering Architecture](image-url)

### Diagram

- **Quantum Buckets**
- **Ingestion Source**
- **Time Ordering**
- **Record Store**

![Figure 3: Record Store Metadata](image-url)
3.4 Retrieval APIs

The LTSS system separates ingress processing and data retrieval across separate processes. Data access is read only; the system does not support insertion or deletion. Records are implicitly deleted/overwritten when storage capacity is exhausted (see Section 4.8 on rolling-around).

Queries can be made programmatically through the Record Reader interface, which provides a standard iterator pattern, C++ API. Data can also be accessed through SQL via the SQLite3 virtual table mechanism [11]. The virtual table implementation backs onto the IRecordReader interface. This presents the data through a table abstraction in which SQL expressions can be applied.

4. IMPLEMENTATION DETAILS

4.1 Component Model

The fundamental building blocks of data pipelines are actors and components. Actors are memory-protected processes that exchange control messages through shared memory. They have at least one thread and typically create new threads for each client connection. Messages, based on Google Protobuf [3], are typed and exchanged by either local IPC or network RPC. Furthermore, actor messages are either synchronous or asynchronous (the latter being typical of a stricter actor model). Actors are composed of components, which are in-process loadable entities that provide typed interfaces and receptacles that can be dynamically inspected and bound (much like Microsoft’s COM architecture [19]). Components do not impose any threading model.

4.2 Zero-Copy Data Plane

Data belonging to flows are exchanged through asynchronous lock-free FIFO queues. Units of data, which we term records, are exchanged between processes in shared memory and are thus zero-copy. Record memory is allocated (producer side) and freed (consumer side) from a thread-safe slab allocator that uses a circular lock-free queue to track slab elements. Both the slab allocator queue and the exchange queue can be configured with SPSC (Single-Producer, Single Consumer) or MPMC (Multi-Producer, Multi-Consumer) queues depending on the requirements of the deployment scenario.

4.3 NIC Actor

The prototype LTSS system operates on UDP/IP (version 4) data packets and makes no assumption about aggregation. IP provides global connectivity while UDP provides a simple protocol for “fire-and-forget” datagram transmission. The current prototype does not use packet authentication or encryption even though this would be likely in a real-world deployment. In our experimentation, our sensor packets are small (< 512 bytes).

4.4 User-Level Network Stack

To maximize network performance, the server-based implementation adopts an exokernel design (see Figure 6) that allows the Network Interface Card (NIC) device driver to fully operate in user-space [1]. In addition to the NIC driver, a lightweight UDP/IP stack also resides in user-space. The advantage of this is improved performance through the elimination of memory copies (both data and control requests) between the kernel and the application. In our experiments, the exokernel approach provides up to three times the performance of the stock kernel network stack. We have not tried an exokernel-based network stack on the embedded platform because we do not have a user-level device driver for non-Intel hardware.

Each NIC device is managed by a single actor. The NIC
actor uses multiple Rx threads to service ingress packet processing for each of the device’s hardware queues (see Figure 7). Load-balancing across queues is achieved through the card’s flow director capability, which uses a selective byte in the packet frame to determine which queue to send the packet to. Each hardware Rx queue also has its own MSI-X interrupt that is routed to a specific core in which the Rx thread is also mapped.

Separate data plane channels are established for each Rx thread in the NIC actor (see Figure 7). The consumer-side is a pipeline actor that incorporates processing elements for sorting, indexing and storing data. This architecture effectively partitions data across multiple pipelines enabling scale-up on multicore systems.

LTSS is portable across platforms. Prototype implementations exist for both Intel-based commodity x86 servers and workstations, as well as embedded ARM platforms (e.g., NVIDIA Jetson TK1, Raspberry Pi). The code is primarily written in C++.

4.5 Persistent Store Metadata

Record data is written either to a file or directly to a block device (without any file system). The latter is useful for integration with a user-level block device driver such as supported by the exokernel. In addition to the record data, the Record Store maintains persistent “block metadata” that holds information about block usage in the storage system, partitioning of resources, record count, record size, etc. The block metadata is written in 4K blocks. N copies of the block metadata are stored on disk, where N is the “rolling count”. Three is typical. When the block device does not support atomic 4K writes, a checksum is used to verify integrity.

4.6 SQLite3 Integration

The LTSS system supports both programmatic and SQL-based query interfaces (see Figure 8). SQL support is realized through the virtual table mechanism [11], which uses a custom loadable library to tailor data storage and retrieval below the SQL query engine. The LTSS virtual table implementation is limited to read-only queries.

The LTSS virtual table implements methods for connection management (xCreate, xConnect, xDisconnect, xDestroy), query plan exploration (xBestIndex), constraint filtering (xFilter), and iterator-based data retrieval (xNext, xEnd, xColumn, xRowid). The underlying record store supports constraints on one or more composite time fields and any other numeric field. Other constraints are delegated to the SQL engine, which can perform filtering above the virtual table implementation.

4.7 Parallel Queries

LTSS supports parallel SQL queries across multiple data partitions (i.e., pipelines). Re-ordering constraints (e.g., ORDER BY) are handled by the SQL engine. The current implementation supports combining results through append operations (i.e., the iterator first exhausts partition A, then partition B and so forth) and sort-merge operations.

4.8 Other Features

Pre-fetching - The system optionally supports using main memory to cache and pre-fetch query results. This can be advantageous to lower selectivity queries. The amount of main memory allocated for pre-fetching is fully configurable.

Storage Roll-around - Because of the simplistic design around record storage, the LTSS can easily “roll-around” the storage so that the oldest records are overwritten by new records according to some total space allocation. The LTSS system supports both file-based or direct (block-level) storage. Direct storage supports allocation of block zones in order to sub-divide the raw block capacity.

Continuous Queries - Current support for continuous queries is limited. The implementation supports the use of callbacks on updates so that the client can be notified when a given number of new records have been inserted. This can be used to trigger summarization or aggregation functions (e.g., over a sliding window) that can be accumulated in a separate table.

5. EVALUATION

To evaluate the performance of the LTSS we used three publicly available data sets: Seismic, Taxi and Energy (see Table 2).

Use of public data, as opposed to proprietary data, enables others to make a fair comparison. Data is taken from archives of actual data and replayed with high-fidelity using our time-series workload generator [12]. For “stress” load generation (i.e., faster than the original source rate) the replay is artificially re-stamped. Data is transmitted from a dedicated generator server across a 10G switched link (see Figure 9). Each data sample is encapsulated in a single IP/UDP packet (i.e., no aggregation occurs).
### 5.2 Ingestion Performance

The first performance measure is ingestion rate in terms of maximum throughput. Maximum throughput is defined as the maximum ingestion rate with zero-packet/record loss and without “delinquent” packets. A packet is considered delinquent when it arrives at the system with a time stamp corresponding to a quantum bucket that has already been closed (i.e., the respective time window has already been passed to the Record Store).

To measure the equivalent network-based ingestion performance of SQLite3 and PostgreSQL, we built wrapper components that can be connected directly to the Channel-Source (refer to Figure 1). Exceeding maximum throughput results in packets being dropped by the NIC-actor (due to blocking on the down-stream components). Measurements were taken for a single pipeline (using wrappers for SQLite3 and PostgreSQL). For PostgreSQL, the records where written with the `COPY` command which inserts records faster than the `INSERT` command. For SQLite, we do not use Write-Ahead Logging (WAL) mode since this will lock out read-access to the database. To perform insertions we used `INSERT` batched using `BEGIN/END` transaction primitives.

Table 4 shows a comparison of ingestion rates for the three data sets (see Table 3) on LTSS and SQLite3. The results show ingestion rates and load index (in brackets). Load index corresponds to the mean sum of CPU load. For example, a load of 2.0 is equivalent to two logical cores 100% active or four cores 50% all of the time. We did not measure the performance of PostgreSQL on the embedded platform since it was not designed with resource constrained environments in mind.

The data shows that LTSS delivers a factor of between 2x and 4x increase in ingestion throughput over the other systems and a rate-per-core improvement factor (calculated by the load index) of between 2x and 3x.

#### 5.2.1 Ingestion Scaling

We also explored the scaling of LTSS ingestion rate with an increasing number of pipelines (and hence data partitions). To do this, we measured ingestion performance of Seismic data up to the maximum sustainable (6 pipelines) by a single NIC card. We chose Seismic data for this test because its small size would best stress the IO handling.

We observed a maximum throughput of 4.33 M records per second with 6 data pipelines (one record per packet) and a load index of 13.47. This corresponds to approxi-
mately 34% system CPU load. We could not increase the number of pipelines without jeopardizing jitter and consequently resulting in packet loss. Figure 10 shows the ingestion scaling for LTSS. Note that the y-axis shows both maximum throughput and load index.

Figure 10: LTSS Ingestion Scaling (multi-pipeline).

### 5.3 Storage Footprint

We measured the on-disk storage footprint (of a clean database) for each of the three data sets. The data schema was the same across each database except that the LTSS exposes multiple logical fields for composite time.

| Data Set | Records | SQLite3 | PostgreSQL | LTSS |
|----------|---------|---------|-------------|------|
| Seismic  | 5.43B   | 179.913 | 246.937     | 186.436 |
| Taxi     | 169.6M  | 29.926  | 32.161      | 23.760  |
| Energy   | 14.7M   | 3.815   | 5.874       | 1.761   |

Table 6: Storage Footprints.

The storage footprints for each data set are given in Table 6. Note, data represents the footprint before queries are performed (i.e., before any storage is used for query caching). The data indicates that LTSS in many cases has a smaller storage footprint than the other two solutions. Of course, compression could also be integrated into LTSS should footprint be of concern.

### 5.4 Memory Footprint

Run-time memory footprint is another important factor to consider. We measured memory footprints for both server and embedded deployments after ingesting 100M records. In all cases we exclude the overhead of the NIC actor and its buffer allocation (~18 MB). We used the default configurations for SQLite3 and PostgreSQL, and buffered records into 4MB chunks for each transaction. For PostgreSQL, we exclude overhead (in the order of hundreds of MB) caused by related processes for check pointing, stats collection, etc. The aim of these measurements is to get an understanding of typical run-time overheads. SQLite3 and PostgreSQL may be configurable with less memory but that likely will change ingestion and query performance.

| Data Set     | SQLite3 (server) | SQLite3 (embedded) | PostgreSQL (server) | LTSS (server) | LTSS (embedded) |
|--------------|------------------|--------------------|---------------------|---------------|-----------------|
|              | ~323 MB          | 35 MB              | ~335 MB             | 27 MB         | 16 MB           |

Table 7: Memory Footprints.

5.5 Out-of-order Tolerance

To examine the tolerance for out-of-order (generally late) packets, we artificially re-stamped packets. We measured the effect on maximum performance for a single pipeline ingesting the Seismic data set. Two modes were measured, adding a fixed delay of 80ms, and adding a random delay of between 1 and 100 ms. Delays were added according to fixed ratios (1:100,1:10,1:5 and 1:2). Table 8 shows the results.

| Ratio   | Max. Throughput (K PPS) |
|---------|-------------------------|
| 80ms    | 1:100                   |
|         | 844.8                   |
|         | 981.5                   |
| 1:10    | 751.0                   |
|         | 713.6                   |
| 1:5     | 748.4                   |
|         | 672.1                   |
| 1:2     | 734.9                   |
|         | 587.6                   |

Table 8: LTSS Out-of-order Tolerance for Seismic Data.

The data indicates that LTSS is reasonably tolerant of out-of-order and would adequately handle expected out-of-order data with little performance degradation.

5.6 Query (Read) Performance

Next, we evaluate SQL query performance. Measurements were taken over 50 consecutive runs on an unloaded system without active queries. The databases were stored on NVMe SSD media via an ext4 file system. The SQLite3 and PostgreSQL database instances include a secondary index for the time column (i.e., using the CREATE INDEX SQL construct). Note that the SQLite3 and PostgreSQL do not support any form of patterned time type and therefore conversion operators need (e.g., EXTRACT and strftime) to be applied at query time. Also, in LTSS, the composite time is derived at ingest time, not at query time.

The results shown in Figure 11 and Figure 12 compare query performance across the three systems for the Taxi and Energy benchmarks (see Appendix for query detail). We focus on these two data sets for evaluation because their queries are more complex and incorporate multiple attributes (e.g., sliding windows).

LTSS is consistently better in terms of query performance and provides significant improvements where the time dimension is highly selective (e.g., Q4 Taxi).

5.7 Query (Read) Performance under Ingestion Load

Finally, we measured the effect of ingest load on query performance (i.e., read-write contention) using the Seismic data set. We chose this data set because of its small record size and thus high packet rate. The test was carried out by applying an aggregation operator (average) over a sliding window query of the last 1000 inserted records. This is given with the following query:
6. CONCLUSIONS

Continued evolution of IoT will bring with it a need to aggregate, process and store large volumes of time-series data. In this paper we have presented a lightweight architecture for storage and indexing of time-series data streams within the context of IoT. Our system, LTSS, is based on a software pipeline architecture that is optimized for multicores processing and parallel IO capabilities. The architecture is specifically designed to take advantage of fast, random-access friendly, non-volatile storage devices (e.g., NVMe) and aims to reduce the dependency on DRAM by simplifying in-memory data structures. The result is a design that can be readily deployed on both commodity server as well as resource constrained and embedded environments.

Our results show a data ingest (completely to persistent store) in the order of 4 million RPS (without UDP packing) for a single 10G NIC with a load index of 14. For the Raspberry Pi 2 embedded platform, we show an ingest capability of around 70K RPS. These results are 3x to 4x improvement over existing RDBMS solutions. We also show that ad-hoc query performance, using SQL, is significantly better than that achievable with two prominent databases, SQLite3 and Postgres. Our solution currently does not employ compression although there is no fundamental reason why this could not be added should a need arise.

We believe that this work represents a first step to considering the increasing shift from IO-bound to CPU-bound data processing and management. Careful consideration of data flow across multiple processor cores and optimized memory management is now becoming a fundamental element of successful high-performance stream processing and storage designs.

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APPENDIX

A. SQLITE3 TAXI DATA BENCHMARK QUERIES

Q1. Count number of pickups after 8pm.
SELECT count(*) FROM TAXIS
WHERE CAST(strftime('H',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) >= 20;
---

Q2. Count number of weekday picks in November 2013.
SELECT count(*) FROM TAXIS
WHERE CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) > 0
AND CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) < 6
AND CAST(strftime('M',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) = 11
AND CAST(strftime('Y',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) = 2013;
---

Q3. Average time of weekday trips in Summer (Jun-Oct).
SELECT avg(trip_time_in_secs) FROM TAXIS
WHERE CAST(strftime('M', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) >= 6
AND CAST(strftime('M', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) <= 10
AND CAST(strftime('W', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) > 0
AND CAST(strftime('W', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) < 6;
---

Q4. Shortest and longest trips on the day of 11/25/2013.
SELECT min(trip_time_in_secs), max(trip_time_in_secs) FROM TAXIS
WHERE CAST(strftime('Y', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) = 2013
AND CAST(strftime('M', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) = 11
AND CAST(strftime('D', pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) = 25;
---

Q5. Total trip distance for a specific vehicle between 9am and 12 noon.
SELECT sum(trip_distance) FROM TAXIS
WHERE CAST(strftime('H',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) >= 9
AND CAST(strftime('H',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) < 12
AND medallion = '5CC9B3C9725FCD7FAE490B4C614D57EE';
---

Q6. Total number of passengers on Saturday and Sunday.
SELECT sum(passenger_count) FROM TAXIS
WHERE CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) == 0
OR CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER) == 6;
---

Q7. Total number of passengers each day of the week.
SELECT CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER),sum(passenger_count) FROM TAXIS
GROUP BY CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER);

B. POSTGRES TAXI DATA BENCHMARK QUERIES

Q1. Count number of pickups after 8pm.
SELECT count(*) FROM TAXI
WHERE EXTRACT(hour FROM pickup_datetime::int4::abstime::timestamp) >= 20;
---

Q2. Count number of weekday picks in November 2013.
SELECT count(*) FROM TAXI
WHERE EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) > 0
AND EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) < 6
AND EXTRACT(month FROM pickup_datetime::int4::abstime::timestamp) = 11
AND EXTRACT(year FROM pickup_datetime::int4::abstime::timestamp) = 2013;
---

Q3. Average time of weekday trips in Summer (Jun-Oct).
SELECT avg(trip_time_in_secs) FROM TAXI
WHERE EXTRACT(month FROM pickup_datetime::int4::abstime::timestamp) >= 6
AND EXTRACT(month FROM pickup_datetime::int4::abstime::timestamp) <= 10
AND EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) > 0
AND EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) < 6;
---

Q4. Shortest and longest trips on the day of 11/25/2013.
SELECT min(trip_time_in_secs), max(trip_time_in_secs) FROM TAXI
WHERE EXTRACT(year FROM pickup_datetime::int4::abstime::timestamp) = 2013
AND EXTRACT(month FROM pickup_datetime::int4::abstime::timestamp) = 11
AND EXTRACT(day FROM pickup_datetime::int4::abstime::timestamp) = 25;
---

Q5. Total trip distance for a specific vehicle between 9am and 12 noon.
SELECT sum(trip_distance) FROM TAXI
WHERE EXTRACT(hour FROM pickup_datetime::int4::abstime::timestamp) >= 9
AND EXTRACT(hour FROM pickup_datetime::int4::abstime::timestamp) < 12
AND medallion = '5CC9B3C9725FCD7FAE490B4C614D57EE';
---

Q6. Total number of passengers on Saturday and Sunday.
SELECT sum(passenger_count) FROM TAXI
WHERE EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) = 0
OR EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp) = 6;
---

Q7. Total number of passengers each day of the week.
SELECT CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER),sum(passenger_count) FROM TAXI
GROUP BY CAST(strftime('W',pickup_datetime, 'unixepoch', 'localtime') AS INTEGER);
SELECT EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp),
sum(passenger_count) FROM TAXI
GROUP BY EXTRACT(dow FROM pickup_datetime::int4::abstime::timestamp);

C. LTSS TAXI DATA BENCHMARK QUERIES

Q1. Count number of pickups after 8pm.
SELECT count(*) FROM TAXI WHERE CTIME_pickup_hour >= 20;
---

Q2. Count number of weekday picks in November 2013.
SELECT count(*) FROM TAXI WHERE CTIME_pickup_wday > 0
AND CTIME_pickup_wday < 6
AND CTIME_pickup_month = 11 AND CTIME_pickup_year = 13;
---

Q3. Average time of weekday trips in Summer (Jun-Oct).
SELECT avg(trip_time_in_secs) FROM TAXI
WHERE CTIME_pickup_month >= 6 AND CTIME_pickup_month <= 10
AND CTIME_pickup_wday > 0 AND CTIME_pickup_wday < 6;
---

Q4. Shortest and longest trips on the day of 11/25/2013.
SELECT min(trip_time_in_secs), max(trip_time_in_secs) FROM TAXI
WHERE CTIME_pickup_year = 13 AND CTIME_pickup_month = 11
AND CTIME_pickup_day = 25;
---

Q5. Total trip distance for a specific vehicle between 9am and 12 noon.
SELECT sum(trip_distance) FROM TAXI WHERE CTIME_pickup_hour >= 9
AND CTIME_pickup_hour < 12
AND medallion = '5CC9B3C9725FCD7FAE490B4C614D57EE';
---

Q6. Total number of passengers on Saturday and Sunday.
SELECT sum(passenger_count) FROM TAXI WHERE CTIME_pickup_wday == 0
OR CTIME_pickup_wday == 6;
---

Q7. Total number of passengers each day of the week.
SELECT CTIME_pickup_wday,sum(passenger_count) FROM TAXI
GROUP BY CTIME_pickup_wday;

D. SQLITE3 ENERGY DATA BENCHMARK QUERIES

Q1. Hourly average power consumption for house H1.
SELECT strftime('%H',DATETIME), avg(V0*I0) FROM POWER
WHERE HOUSEID = 'H1' GROUP BY strftime('%H',DATETIME);
---

Q2. Maximum power sample for each house.
SELECT HOUSEID, max(V0*I0) FROM POWER
WHERE CAST(strftime('%H',DATETIME) AS INTEGER) > 8 AND CAST(strftime('%H',DATETIME) AS INTEGER) <= 20
GROUP BY HOUSEID ORDER BY HOUSEID;
---

Q3. Highest hourly average power sample point for each house.
WITH
    hourlies (HOUSEID, HOUR, POWER) AS (SELECT HOUSEID, strftime('%H',DATETIME), avg(V0*I0) FROM POWER
GROUP BY HOUSEID, strftime('%H',DATETIME) ORDER BY avg(V0*I0) DESC)
SELECT HOUSEID, HOUR, max(POWER) FROM hourlies
WHERE HOUSEID IN (SELECT DISTINCT HOUSEID FROM POWER)
---

Q4. Top ten, 5 minute periods of consumption from house ‘H1’ (tumbling window).
SELECT HOUSEID, avg(V0*I0), (strftime('%s',DATETIME)/300) FROM POWER
WHERE HOUSEID='H1' GROUP BY HOUSEID, (strftime('%s',DATETIME)/300) ORDER BY (strftime('%s',DATETIME)/300) DESC LIMIT 10;
---

Q5. Number of samples between two datetimes
SELECT count(*) FROM POWER WHERE DATETIME >= '2012-07-30 09:35:00' AND DATETIME <= '2012-07-30 09:39:00';
---

Q6. Average maximum weekday consumption for each house.
WITH
    weekday_max(houseid, wdaymax, power)
AS (
    SELECT HOUSEID, strftime('%w',DATETIME), max(V0*I0)
    FROM POWER
    GROUP BY HOUSEID, strftime('%w',DATETIME)
)
SELECT houseid, avg(power) FROM weekday_max GROUP BY houseid ORDER BY houseid;
---

Q7. Number of samples taken between 5pm and 9pm on Wednesday.
SELECT count(*) FROM POWER WHERE strftime('%w',DATETIME) = '3'
AND CAST(strftime('%w',DATETIME) as INTEGER) >= 17 AND CAST(strftime('%w',DATETIME) as INTEGER) <= 20;

E. POSTGRES ENERGY DATA BENCHMARK QUERIES
Q1. Hourly average power consumption for house H1.
SELECT EXTRACT(hour FROM DATETIME), avg(V0 * I0) FROM POWER
WHERE HOUSEID = 'H1' GROUP BY EXTRACT(hour FROM DATETIME);
---
Q2. Maximum power sample for each house.
SELECT HOUSEID, max(V0*I0) FROM POWER
WHERE EXTRACT(hour FROM DATETIME) > 8 AND EXTRACT(hour FROM DATETIME) <= 20
GROUP BY HOUSEID ORDER BY HOUSEID;
---
Q3. Highest hourly average power sample point for each house.
WITH hourlies (HOUSEID, HOUR, POWER) AS (SELECT HOUSEID, EXTRACT(hour FROM DATETIME), avg(V0 * I0)
FROM POWER
ORDER BY HOUSEID, EXTRACT(hour FROM DATETIME)
SELECT * FROM ( SELECT DISTINCT ON (HOUSEID) * FROM hourlies ORDER BY HOUSEID ) q
ORDER BY q.houseid;
---
Q4. Top ten, 5 minute periods of consumption from house ‘H1’ (tumbling window).
WITH fives(houseid, avgpower) AS {
SELECT HOUSEID, avg(V0*10) FROM POWER
WHERE HOUSEID='H1'
GROUP BY HOUSEID, (cast(EXTRACT(EPOCH FROM DATETIME) as int)/300)
ORDER BY HOUSEID }
SELECT fives.houseid, avgpower FROM fives ORDER BY fives.avgpower DESC LIMIT 10;
---
Q5. Number of samples between two datetimes
SELECT count(*) FROM POWER WHERE DATETIME >= '2012-07-30 09:35:00'
AND DATETIME <= '2012-07-30 09:39:00';
---
Q6. Average maximum weekday consumption for each house.
WITH weekday_max(houseid, wdaymax, power) AS (SELECT HOUSEID, EXTRACT(dow FROM DATETIME), max(V0*I0)
FROM POWER GROUP BY HOUSEID, EXTRACT(dow FROM DATETIME)
) 
SELECT houseid, avg(power) FROM weekday_max GROUP BY houseid ORDER BY houseid;
---
Q7. Number of samples taken between 5pm and 9pm on Wednesday.
SELECT count(*) FROM POWER WHERE EXTRACT(dow FROM DATETIME) = 3 AND EXTRACT(hour FROM DATETIME) >= 17
AND EXTRACT(hour FROM DATETIME) <= 20;

F. LTSS ENERGY DATA BENCHMARK QUERIES
Q1. Hourly average power consumption for house H1.
SELECT CTIME_hour, avg(V0*I0) FROM POWER WHERE HOUSEID = 'H1'
GROUP BY CTIME_hour ORDER BY CTIME_hour;
---
Q2. Maximum power sample for each house.
SELECT HOUSEID, max(V0*I0) FROM POWER
WHERE CTIME_hour > 8 AND CTIME_hour < 20 GROUP BY HOUSEID ORDER BY HOUSEID;
---
Q3. Highest hourly average power sample point for each house.
WITH hourlies (HOUSEID, HOUR, POWER) AS (SELECT HOUSEID, CTIME_hour, avg(V0*I0)
FROM POWER GROUP BY HOUSEID, CTIME_hour ORDER BY avg(V0*I0) DESC)
SELECT hourlies.houseid, max(hourlies.power) FROM hourlies
WHERE HOUSEID IN (SELECT DISTINCT HOUSEID FROM POWER) GROUP BY HOUSEID;
---
Q4. Top ten, 5 minute periods of consumption from house ‘H1’ (tumbling window).
SELECT HOUSEID, avg(V0*I0), (TIMESTAMP / 300000000) FROM POWER
WHERE HOUSEID='H1' (TIMESTAMP / 300000000) DESC LIMIT 10;
---
Q5. Number of samples between two datetimes
SELECT count(*) FROM POWER WHERE CTIME_year = 12 AND CTIME_month = 7
AND CTIME_day = 30 AND CTIME_hour = 9 AND CTIME_min >= 35 AND CTIME_min < 39;
---
Q6. Average maximum weekday consumption for each house.
WITH weekday_max(houseid, wdaymax, power) AS (SELECT HOUSEID, CTIME_wday, max(V0*I0)
FROM POWER GROUP BY HOUSEID, CTIME_wday ORDER BY avg(V0*I0) DESC)
SELECT houseid, avg(power) FROM weekday_max
WHERE CTIME_wday = 3 AND CTIME_hour >= 17
AND CTIME_hour <= 20;
---
Q7. Number of samples taken between 5pm and 9pm on Wednesday.
SELECT count(*) FROM POWER WHERE CTIME_wday = 3 AND CTIME_hour >= 17
AND CTIME_hour <= 20;