The RADStack: Open Source Lambda Architecture for Interactive Analytics

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ABSTRACT

The Real-time Analytics Data Stack, colloquially referred to as the RADStack, is an open-source data analytics stack designed to provide fast, flexible queries over up-to-the-second data. It is designed to overcome the limitations of either a purely batch processing system (which takes too long to surface new events) or a purely real-time system (which is difficult to ensure that no data is left behind and there is often no way to correct data after initial processing). It will seamlessly return best-effort results on very recent data combined with guaranteed-correct results on older data. In this paper, we introduce the architecture of the RADStack and discuss our methods of providing interactive analytics and a flexible data processing environment to handle a variety of real-world workloads.

1. INTRODUCTION

The rapid growth of the Hadoop[19] ecosystem has enabled many organizations to flexibly process and gain insights from large quantities of data. These insights are typically business intelligence questions, or OnLine Analytical Processing (OLAP) queries. Hadoop has proven to be an extremely effective framework capable of providing many analytical insights and is able to solve a wide range of distributed computing problems. However, as much as Hadoop is lauded for its wide range of use cases, it is derided for its high latency in processing and returning results. A common approach to surface data insights is to run MapReduce jobs that may take several hours to complete.

Data analysis and data-driven applications are becoming increasingly important in industry, and the long query times seen with using frameworks such as Hadoop are becoming increasingly intolerable. User facing applications are replacing traditional reporting interfaces as the preferred means for organizations to derive value from their datasets. In order to provide an interactive user experience, user interactions with data-driven applications must complete in an order of milliseconds. Because most of these interactions revolve around data exploration and computation, organizations quickly realized that in order support low latency queries, dedicated serving layers are necessary. Today, most of these serving layers are Relational Database Management Systems (RDBMS) or NoSQL key/value stores. Neither RDBMS nor NoSQL key/value stores are particularly designed for analytics, but these technologies are still frequently selected as serving layers because of their general popularity. Hence, solutions that involve these technologies can be inflexible, or suffer from architecture drawbacks that prevent them from returning queries fast enough to power interactive, user-facing applications [22].

An ideal serving layer by itself is still insufficient as a complete analytics solution. In most real-world use cases, raw data cannot be directly stored in the serving layer. Raw data suffers from many imperfections and must first be processed (transformed, or cleaned) before it is usable. Hadoop remains a popular option to process raw data and many organizations first process raw data in Hadoop before loading the result into the serving layer. The drawback of this approach is that loading and processing batch data is slow, and insights on events are often obtained hours after the events have occurred [].

To address the problem of delays in data freshness caused by batch processing frameworks, numerous open-source stream processing frameworks such as Apache Storm[16], Apache Spark Streaming[24], and Apache Samza[1] have been gaining popularity for offering a low-latency model to ingest and process event streams. These stream processing frameworks have enabled data processing at near real-time speeds. The drawback of popular open-source stream processors is that they do not necessarily provide the same correctness guarantees as batch processing frameworks. Events can come in days late, and may need to be corrected after the fact. Large blocks of data may also need to be reprocessed at any time as new columns are added or removed.

The RADStack is an open source, end-to-end solution meant to offer flexible, low-latency analytic queries on near real-time data. The solution combines the low latency guarantees of stream processors and the correctness and flexibility guarantees of batch processors. It also introduces a serving layer specifically designed for interactive analytics. The stack's main building blocks are Apache Kafka[13], Apache Samza, Apache Hadoop, and Druid[], and we've found that the combination of technologies is flexible enough to handle a wide variety of processing requirements and query loads. Each piece of the stack is designed to do a specific set of things very well. This paper will cover the details and design principles of the RADStack. Our contributions are around the architecture of the stack itself, the introduction of Druid as a serving layer, and our model for unifying real-time and historical workflows.

The structure of the paper is as follows: Section 2 describes the problems and use cases that led to the creation of the RADStack. Section 3 describes Druid, the serving layer of the stack, and how Druid is built for real-time and batch data ingestion, as well as exploratory analytics. Section 4 covers the role of Samza and Hadoop for data processing, and Section 5 describes the role of Kafka for event delivery. In Section 6, we present our production metrics. Section 7 presents our experiences with running the RADStack in production, and in Section 8 we discuss the related work.

2. BACKGROUND

The development of RADStack came about iteratively. Different technologies were introduced to address various problems and use cases that came up over time. The initial concept of the RADStack started at Metamarkets, an analytics startup focused in the advertising technology space, and has since been adopted by other technology companies [2]. In the early days of Metamarkets, we wanted to build an analytics dashboard where users could arbitrarily explore their data. An example of the data found in online advertising space is shown in Table 1. An example dashboard is shown in Figure [].

The data shown in Table 1 is fairly standard in OLAP workflows. The data is transactional (timeseries data) and tends to be very append heavy. Each event is comprised of three components: a timestamp indicating when the event occurred; a set of dimensions indicating various attributes about the event; and a set of metrics concerning the event. Our goal is to rapidly compute drill-down and aggregates with this data, to answer questions such as "How many clicks occurred over the span of one week for publisher google.com?" or "How many impressions were seen over the last quarter from the city of San Francisco?" We wanted to issue queries over any arbitrary number of dimensions and have results return in at most several hundred milliseconds.

In addition to the query latency needs, we needed to support multi-tenancy. User-facing applications often face highly concurrent workloads and good applications need to provide relatively consistent performance to all users. Finally, we needed our backend infrastructure to be highly available. Downtime is costly and many businesses cannot afford to wait if a system is unavailable in the face of software upgrades or network failure. Downtime for startups, who often lack proper internal operations management, can determine business success or failure.

Following industry standard practices, we evaluated various options for a serving layer. We tried to select a serving layer that was optimized for the types of queries we wanted to make, and we initially began our experiments with PostgreSQL[21]. Our setup with PostgreSQL followed the common conventions of using RDBMSs as data warehouses. We modeled the advertising data using a star schema, we had a set of aggregate tables to increase aggregation performance, and we had a query cache to further speed up queries.

Our findings with PostgreSQL are shown in Table 2. Query latencies were generally acceptable if the results were cached, less acceptable if we hit aggregate tables, and unacceptable if we needed to scan the base fact table. A single page load of the first version of our application, which issued about 20 concurrent queries to the serving layer and only required aggregating a few metrics, took several minutes to complete. This was too slow to power an interactive application. We quickly realized a row store, and relational model as a whole, was a sub-optimal choice for the application we were trying to build.

We next evaluated HBase [10], a NoSQL key/value store. As is common with using key/value stores, we precomputed the total set of queries we anticipated users would make. An example of this precomputation is shown in Figure []. Our results with HBase are shown in Table []. Queries were obviously fast as we were effectively doing O(1) lookups into maps. However, the solution was not particularly flexible; if something precomputed, it wasn't queryable, and the precomputation time became an incredible pain point. We attempted to build iceberg cubes as described in [], restricting the space of our pre-computations, but even then the precomputation times were unbearably slow. Our entire evaluation of both RDBMS and key/value stores is described in detail in [22].

Druid was developed in an attempt to solve some of the problems seen with traditional serving layers. Druid was designed from the ground up to provide arbitrary data exploration, low latency aggregations, and fast data ingestion. Druid was also designed to intake fully denormalized data, and moves away from the traditional relational model. Since much of raw data is not denormalized, it must be processed before it can be ingested and queried. Multiple streams of data had to be joined, cleaned up, and transformed before it was usable in Druid, but that was the trade-off we decided was necessary in order to get the performance necessary for an interactive data application. We introduced stream processing to our stack to provide the business logic processing that was required before raw data could be loaded into Druid. Our streaming processing jobs range from simple data transformations, such as id to name lookups, up to complex operations such as multi-stream joins. Pairing Druid with a stream processor enabled flexible data processing and querying, but because events were delivered from many different locations and sources, we also required technology that was designed for high throughput event delivery. Thus, we added Kafka to our stack, and Kafka became the event delivery endpoint for our clients. Kafka provided a highly available message bus. Samza read data from Kafka, processed it, and delivered the output to Druid.

Our stack would be complete here if real-time processing were perfect. Sadly, the open source stream processing space is still young. Processing jobs can go down for extended periods of time and events may be delivered more than once. These are realities of any production data pipeline. To overcome these issues, we included Hadoop in our stack

Timestamp	Publisher	Advertiser	Gender	City	Click	Price
2011-01-01T01:01:35Z	bieberfever.com	google.com	Male	San Francisco	0	0.65
2011-01-01T01:03:63Z	bieberfever.com	google.com	Male	Waterloo	0	0.62
2011-01-01T01:04:51Z	bieberfever.com	google.com	Male	Calgary	1	0.45
2011-01-01T01:00:00Z	ultratrimfast.com	google.com	Female	Taiyuan	0	0.87
2011-01-01T02:00:00Z	ultratrimfast.com	google.com	Female	New York	0	0.99
2011-01-01T02:00:00Z	ultratrimfast.com	google.com	Female	Vancouver	1	1.53

Table 1: Sample ad data. These events are created when users view or click on ads.

Native Benchmark Scan Rate	5.5M rows/second/core
1 day of summarized aggregates	60M+ rows
1 query over 1 week, 16 cores	5 seconds
Page load with 20 queries over a week of data	several minutes

Table 2: Initial evaluation with PostgreSQL on m2.2xlarge EC2 node.

to periodically clean up any data generated by the real-time pipeline. We stored a copy of the raw events we received in a distributed file system, and periodically ran batch processing jobs over this data. The high level architecture of our setup is shown in Figure [], and illustrates the pieces of the RADStack. Each component in the RADStack is designed to do a specific set of things well, and there is isolation in terms of functionality. Individual components can entirely fail without impacting the services of the other components.

3. THE SERVING LAYER

Druid acts as the serving layer in the RADStack. Druid is a column-oriented data store designed for exploratory analytics. A Druid cluster consists of different types of nodes and, similar to the overall design of the RADStack, each node type is instrumented to perform a specific set of things well. We believe this design separates concerns and simplifies the complexity of the overall system. The different node types operate fairly independent of each other and there is minimal interaction among them. Hence, intra-cluster communication failures have minimal impact on data availability. To solve complex data analysis problems, the different node types come together to form a fully working system. The composition of and flow of data in a Druid cluster are shown in Figure 1.

3.1 Segments

Data tables in Druid (called data sources) are collections of timestamped events and partitioned into a set of segments, where each segment is typically 5–10 million rows. We define a segment as a collection of rows of data that span some period of time. Segments represent the fundamental storage unit in Druid and Druid queries only understand how to scan segments.

Druid always requires a timestamp column as a method of simplifying data distribution policies, data retention policies, and first level query pruning. Druid partitions its data sources into well defined time intervals, typically an hour or a day, and may further partition on values from other columns to achieve the desired segment size. The time granularity to partition segments is a function of data volume and time range. A data set with timestamps spread over a year is better partitioned by day, and a data set with timestamps spread over a day is better partitioned by hour.

Segments are uniquely identified by a data source identifier, the time interval of the data, and a version string that increases whenever a new segment is created. The version string indicates the freshness of segment data; segments with later versions have newer views of data (over some time range) than segments with older versions. This segment metadata is used by the system for concurrency control; read operations always access data in a particular time range from the segments with the latest version identifiers for that time range.

Druid segments are stored in a column orientation. Given that Druid is best used for aggregating event streams (all data going into Druid must have a timestamp), the advantages of storing aggregate information as columns rather than rows are well documented [3]. Column storage allows for more efficient CPU usage as only what is needed is actually loaded and scanned. In a row oriented data store, all columns associated with a row must be scanned as part of an aggregation. The additional scan time can introduce significant performance degradations [3].

Druid nodes use one thread to scan one segment at a time, and the amount of data that can be scanned in parallel is directly correlated to the number of available cores in the cluster. Segments are immutable, and immutability confers a few advantages. Immutable segments enable read consistency, and multiple threads can scan the same segment at the same. This helps enable higher read throughput.

A single query may require scanning thousands of segments concurrently, and many queries may run at the same time. We want to ensure that the entire cluster is not starved out while a single expensive query is executing. Thus, segments have an upper limit in how much data they can hold, and are designed to be scanned in a few milliseconds. By keeping segment computation very fast, cores and other resources are constantly being yielded.This ensures segments from different queries are always being scanned.

Druid segments are very self-contained for the time interval of data that they hold. Column data is stored directly in the segment. Druid has multiple column types to represent various data formats. For typical OLAP data, timestamps are stored in long columns, dimensions are stored in string columns, and measures (or metrics as they are called in Druid) are stored in int, float, long or double columns. Depending on the column type, different compression methods may be used. Metric columns are compressed using LZ4 [] compression. String columns are dictionary encoded, similar to other data stores such as PowerDrill[11]. Additional indexes may be created for particular columns. For exam-

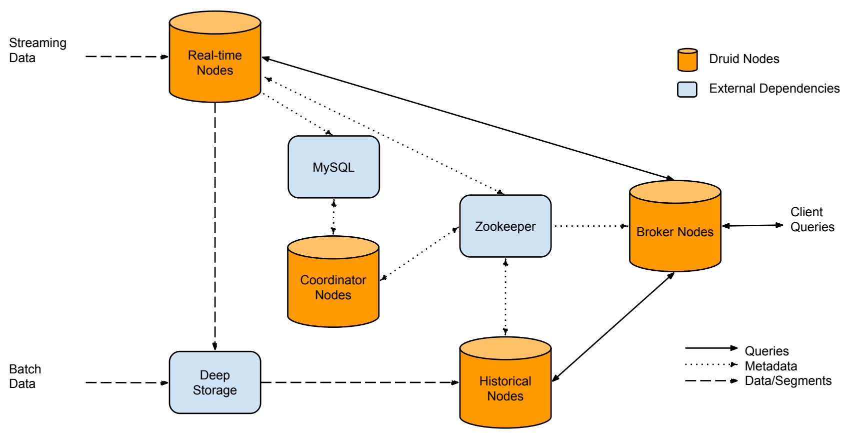


Figure 1: An overview of a Druid cluster and the flow of data through the cluster.

ple, Druid will by default create inverted indexes for string columns.

3.2 Exploratory Analytics

Real-world OLAP queries often ask for the aggregated totals for some set of metrics, filtered for some boolean expressions of dimension specifications, over some period of time. An example query for Table 1 may ask: "How many clicks occurred where publisher is bieberfever.com and users were male?".

Consider the publisher column in Table 1, a string column. For each unique publisher in Table 1, our inverted index tells us in which table rows a particular page is seen. Our inverted index looks like the following:

```
bieberfever.com   -> rows [0, 1, 2] -> [1][1][1][0][0][0]
ultratrimfast.com -> rows [3, 4, 5] -> [0][0][0][1][1][1]
```

In the binary array, the array indices represent our rows, and the array values indicate whether a particular value was seen. In our example, bieberfever.com is seen in rows 0, 1 and 2. To know which rows contain bieberfever.com or ultratrimfast.com, we can OR together the two arrays.

```
[1][1][1][0][0][0] OR [0][0][0][1][1][1] = [1][1][1][1][1][1]
```

Our query is aggregating two metrics. Our metrics are also stored in a column orientation such as the following:

```
Clicks -> [0, 0, 1, 0, 0, 1]
Price  -> [0.65, 0.62. 0.45, 0.87, 0.99, 1.53]
```

We can quickly load up only the metric columns we need for the query. We do not need to scan the entire metric column for a given query. For example, queries for results where publisher is bieberfever.com only requires scanning rows 0, 1, and 2 in the metrics column. The inverted indexes tell us exactly the rows we need to scan, and Druid has an internal cursor to only walk through the rows that match the final inverted index.

3.3 Streaming Data Ingestion

Druid real-time nodes encapsulate the functionality to ingest and query event streams. Events indexed via these nodes are immediately available for querying. The nodes are only concerned with events for some small time range

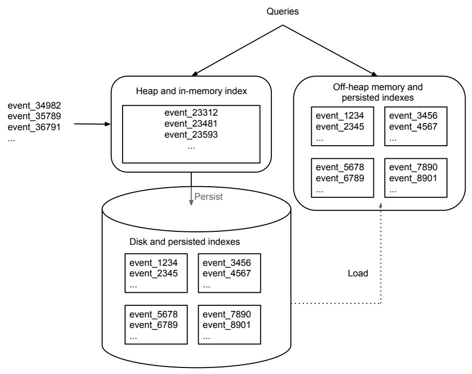


Figure 2: Real-time nodes buffer events to an in-memory index, which is regularly persisted to disk. On a periodic basis, persisted indexes are then merged together before getting handed off. Queries will hit both the in-memory and persisted indexes.

and periodically hand off immutable batches of events they have collected over this small time range to other nodes in the Druid cluster that are specialized in dealing with batches of immutable events. The nodes announce their online state and the data they serve in Zookeeper[12].

Real-time nodes employ a log structured merge tree[17] for recently ingested data. Incoming events are first stored in an in-memory buffer. The in-memory buffer is directly queryable and Druid behaves as a row store for queries on events that exist in this JVM heap-based store. The in-memory buffer is heavily write optimized, and given that Druid is really designed for heavy concurrent reads, events do not remain in the in-memory buffer for very long. To avoid heap overflow problems and to improve read latency, real-time nodes persist their in-memory indexes to disk either periodically or after some maximum row limit is reached. This persist process converts data stored in the in-memory buffer to the column oriented segment storage format described in Section 3.1. Persisted segments are memory mapped and loaded into off-heap memory such that they can still be queried. This is illustrated in Figure 3. Data is continuously queryable during the persist process.

Real-time ingestion in Druid is self-throttling. If a significant spike occurs in the number of events transferred from the upstream event producer, there are a few safety mechanisms built in. Recall that events are first stored in an in-memory buffer and persists can occur when a maximum configurable row limit is reached. Spikes in event volume should cause persists to occur more often and not overflow the in-memory buffer. However, the process of building a segment does require time and resources. If too many concurrent persists occur, and if events are added to the in-memory buffer faster than they can be removed through the persist process, problems can still arise. Druid sets a limit on the maximum number of persists that can occur at a time, and if this limit is reached, Druid will begin to throttle event ingestion. In this case, the onus is on the upstream consumer to be resilient in the face of increasing backlog.

Real-time nodes store recent data for a configurable period of time, typically an hour. This period is referred to as the segment granularity period. The nodes employ a sliding window to accept and reject events and use the wall-clock time as the basis of the window. Events within a configurable limit before or after the node's wall-clock time are accepted, and events outside this window are dropped. This period is referred to as the window period and typical window periods are 10 minutes in length. The window period is illustrated in Figure []. At the end of the segment granularity period plus the window period, a real-time node will hand off the data it has collected during the segment granularity period.

For further clarification, consider Figure 3. Figure 3 illustrates the operations of a real-time node. The node starts at 13:37 and, with a 10 minute window period, will only accept events for a window between 13:17 and 13:47. When events are ingested, the node announces that it is serving a segment of data for an interval from 13:00 to 14:00. Every 10 minutes (the persist period is configurable), the node will flush and persist its in-memory buffer to disk. Near the end of the hour, the node will likely see events for 14:00 to 15:00. When this occurs, the node prepares to serve data for the next hour and creates a new in-memory buffer. The node then announces that it is also serving a segment from 14:00 to 15:00. The node does not immediately merge persisted indexes from 13:00 to 14:00, instead it waits for a configurable window period for straggling events from 13:00 to 14:00 to arrive. This window period minimizes the risk of data loss from delays in event delivery. At the end of the window period, the node merges all persisted indexes from 13:00 to 14:00 into a single immutable segment and hands the segment off. Once this segment is loaded and queryable somewhere else in the Druid cluster, the real-time node flushes all information about the data it collected for 13:00 to 14:00 and unannounces it is serving this data.

The use of the window period means that events that are substantially delayed will be dropped. In practice, we see that these occurrences are rare, but they do occur. Druid's real-time logic does not guarantee exactly once processing and is instead best effort. The lack of exactly once processing in Druid is one of the motivations for requiring batch fix up in the RADStack.

3.4 Hand off

Real-time nodes are designed to deal with a small window of recent data and need periodically hand off segments they've built. The hand-off process first involves a compaction step. The compaction process finds all the segments that were created for a specific interval of time (for example, all the segments that were created by intermediate persists over the period of an hour). These segments are merged together to form a final immutable segment for handoff.

Handoff occurs in a few steps. First, the finalized segment is uploaded to a permanent backup storage, typically a distributed file system such as S3 [] or HDFS [], which Druid refers to as "deep storage". Next, an entry is created in the metadata store (typically a RDBMS such as MySQL) to indicate that a new segment has been created. This entry in the metadata store will eventually cause other nodes in the Druid cluster to download and serve the segment. The real-time node continues to serve the segment until it notices that the segment is available on Druid historical nodes, which are nodes that are dedicated to serving historical data. At this point, the segment is dropped and unannounced from the real-time node. The entire handoff process is fluid; data remains continuously queryable throughout the entire handoff process. Segments created by real-time processing are versioned by the start of the segment granularity interval.

3.5 Batch Data Ingestion

The core component used by real-time ingestion is an index that can be incrementally populated and finalized to create an immutable segment. This core component is shared across both real-time and batch ingestion. Druid has built in support for creating segments by leveraging Hadoop and running MapReduce jobs to partition data for segments. Events can be "streamed" directly from static files.

Similar to the real-time ingestion logic, segments created through batch ingestion are directly uploaded to deep storage. Druid's Hadoop-based batch indexer will also create an entry in the metadata storage once all segments have been created. The version of the segments created by batch ingestion are based on the time the batch processing job starts at.

3.6 Unifying Views

When new entries are created in the metadata storage, they will eventually be noticed by Druid coordinator nodes. Druid coordinator nodes poll the metadata storage for what segments should be loaded on Druid historical nodes, and compare the result with what is actually loaded on those nodes. Coordinator nodes will tell historical nodes to load new segments, drop outdated segments, and move segments across nodes.

Druid historical nodes are very simple in operation. They know how to load, drop, and respond to queries that scan segments. Historical nodes typically store all the data that is older than an hour (recent data lives on the real-time node). The real-time handoff process requires that a historical must load first load and begin serving queries for a segment before that segment can be dropped from the real-time node. Since segments are immutable, the same copy of a segment can exist on multiple historical nodes and real-time nodes. Most nodes in typical production Druid clusters are historical nodes.

To consolidate results from historical and real-time nodes, Druid has a set of broker nodes which act as the endpoint

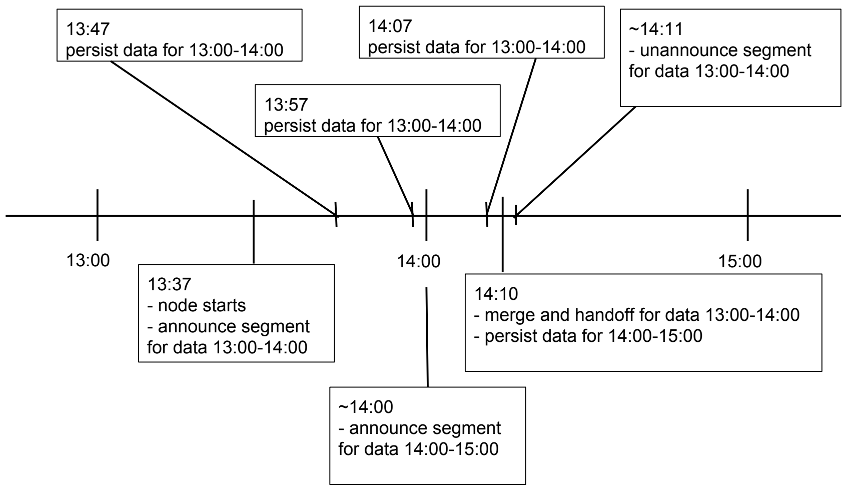


Figure 3: The node starts, ingests data, persists, and periodically hands data off. This process repeats indefinitely. The time periods between different real-time node operations are configurable.

that clients query. Broker nodes function as query routers to historical and real-time nodes. Broker nodes understand the metadata published in Zookeeper about what segments are queryable and where those segments are located. Broker nodes route incoming queries such that the queries hit the right historical or real-time nodes. Broker nodes also merge partial results from historical and real-time nodes before returning a final consolidated result to the caller.

Broker nodes maintain a segment timeline containing information about what segments exist in the cluster and the version of those segments. Druid uses multi-version concuncurrency control to manage how data is extracted from segments. Segments with higher version identifiers have precedence over segments with lower version identifiers. If two segments exactly overlap for an interval, Druid only considers the data from the segment with the higher version interval.

Segments are inserted into the timeline as they are announced. The timeline sorts the segment based on their data interval in a data structure similar to an interval tree. Lookups in the timeline will return all segments with intervals that overlap the lookup interval, along with interval ranges for which the data in a segment is valid. This is illustrated in Figure [].

Brokers extract the interval of a query and use it for lookups into the timeline. The result of the timeline is used to remap the original query into a set of specific queries for the actual historical and real-time nodes that hold the pertinent query data. This process is illustrated in Figure[]. The results from the historical and real-time nodes are finally merged by the broker, which returns the final result to the caller.

The coordinator node also builds a segment timeline for segments in the cluster. If a segment is completely overshadowed by one or more segments, it will be flagged in this timeline. When the coordinator notices overshadowed segments, it tells historical nodes to drop these segments from the cluster.

3.7 Supported Queries

Druid has its own query language and accepts queries as POST requests. Broker, historical, and real-time nodes all share the same query API.

The body of the POST request is a JSON object containing key/value pairs specifying various query parameters. A typical query will contain the data source name, the granularity of the result data, time range of interest, the type of request, and the metrics to aggregate over. The result will also be a JSON object containing the aggregated metrics over the time period.

Most query types will also support a filter set. A filter set is a Boolean expression of dimension name and value pairs. Any number and combination of dimensions and values may be specified. When a filter set is provided, only the subset of the data that pertains to the filter set will be scanned. The ability to handle complex nested filter sets is what enables Druid to drill into data at any depth.

The exact query syntax depends on the query type and the information requested. A sample count query over a week of data is as follows:

```
{
  "queryType": "timeseries",
  "dataSource": "ads",
  "intervals": "2013-01-01\/2013-01-08",
  "filter": {
    "type": "selector",
    "dimension": "publisher",
    "value": "google.com"
  },
  "granularity": "day",
  "aggregations": [
    {
      "type": "count",
      "name": "rows"
    }
  ]
}
```

The query shown above will return a count of the number of rows in the "ads" data source from 2013-01-01 to 2013-01-08, filtered for only those rows where the value of the “publisher” dimension is equal to “google.com”. The results will be bucketed by day and will be a JSON array of the following form:

```
[
  {
    "timestamp": "2012-01-01T00:00:00.000Z",
    "result": {
      "rows": 393298
    }
  },
  {
    "timestamp": "2012-01-02T00:00:00.000Z",
    "result": {
      "rows": 382932
    }
  },
  ...
  {
    "timestamp": "2012-01-07T00:00:00.000Z",
    "result": {
      "rows": 1337
    }
  }
]
```

Druid supports many types of aggregations including sums on floating-point and integer types, minimums, maximums, and complex aggregations such as cardinality estimation and approximate quantile estimation. The results of aggregations can be combined in mathematical expressions to form other aggregations. It is beyond the scope of this paper to fully describe the query API but more information can be found online[1].

As of this writing, a join query for Druid is not yet implemented. This has been a function of engineering resource allocation and use case decisions more than a decision driven by technical merit. Indeed, Druid's storage format would allow for the implementation of joins (there is no loss of fidelity for columns included as dimensions) and the implementation of them has been a conversation that we have every few months. To date, we have made the choice that the implementation cost is not worth the investment for our organization. The reasons for this decision are generally two-fold.

1. Scaling join queries has been, in our professional experience, a constant bottleneck of working with distributed databases.
2. The incremental gains in functionality are perceived to be of less value than the anticipated problems with managing highly concurrent, join-heavy workloads.

A join query is essentially the merging of two or more streams of data based on a shared set of keys. The primary high-level strategies for join queries we are aware of are a hash-based strategy or a sorted-merge strategy. The hash-based strategy requires that all but one data set be available as something that looks like a hash table, a lookup operation is then performed on this hash table for every row in the “primary” stream. The sorted-merge strategy assumes that each stream is sorted by the join key and thus allows for the incremental joining of the streams. Each of these strategies, however, requires the materialization of some number of the streams either in sorted order or in a hash table form.

When all sides of the join are significantly large tables ($>$ 1 billion records), materializing the pre-join streams requires complex distributed memory management. The complexity of the memory management is only amplified by the fact that we are targeting highly concurrent, multi-tenant workloads. For these reasons, we've elected to do joins at the processing layer for the time being.

[1]http://druid.io/docs/latest/Querying.html

4. THE PROCESSING LAYER

Although Druid can ingest events that are streamed in one at a time, data must be denormalized before it is ingested in Druid, as Druid cannot yet support join queries. Furthermore, real world data must often be transformed before it is usable by an application.

4.1 Stream Processing

Stream processors provide infrastructure to develop processing logic for unbounded sequences of tuples. We will focus our discussions on Apache Samza as our stream processor, although other technologies are viable alternatives. Samza provides an API to write jobs that run over a sequence of tuples and perform operations over those tuples in a user-defined way. The input to each job is provided by Kafka, which can also act as a sink for the output of the job. Samza jobs are executed in a resource management and task execution framework such as YARN []. It is beyond the scope of this paper to go into the full details of Kafka/YARN/Samza interactions, but more information is available in other literature []. We will instead focus on how we leverage this framework for processing data for analytic use cases.

On top of Samza infrastructure, we introduce the idea of a “pipeline”, which is a grouping for a series of related processing jobs, sorted in some logical order. The output of one job may act as the input for the next job. Some of our jobs involve operations include renaming data, inserting default values for nulls and empty strings, and filtering data. One pipeline maps logically to one data source in Druid.

Given that Druid does not support joins in queries, we require supporting joins at the data processing level. Our approach to do streaming joins is to leverage a key/value store such as Redis[] and buffer events in memory for a given period of time. If an event arrives in the system with a join key that exists in the key/value store, the join occurs and the joined event is transmitted further down the pipeline. If events are substantially delayed and do not arrive in the allocated window period, the original event is dropped. This means that our stream processing layer is not guaranteed to deliver 100accurate results. Furthermore, Samza does not offer exactly-once processing semantics. Problems in network connectivity or node failure can lead to duplicated events. For this reason, we run a separate batch pipeline that will generate an accurate copy of the ingested data.

The final job in our processing pipeline is to deliver data to Druid. For high availability, processed events from Samza are transmitted concurrently to two real-time nodes. Both nodes receive the same copy of data, and one node effectively acts as a replica. The Druid broker does not distinguish between the two copies of data, and queries will go to either node. When handoff occurs, both real-time nodes race to hand off the segments they've created. The segment that is pushed into deep storage first will be the one that is used for historical querying, and once that segment is loaded on the historical nodes, both real-time nodes will drop their versions of the same segment.

4.2 Batch Processing

Our batch processing pipeline is composed of two stages. The first stage mirrors our streaming processing pipeline in that it transforms data and joins relevant events in preparation for the is data to be loaded into Druid. This is done via a MapReduce job, similar to the setup described in []. The second stage of batch processing is responsible for directly creating immutable Druid segments. We can run a second MapReduce[6] job that feeds reads our processed data from the first stage and loads this data into Druid's built in ingestion logic. The ingestion code for both streaming and batch ingestion in Druid is shared between the two modes of ingestion. The batch processing logic uploads these segments to deep storage, and writes a new entry in the metadata store to indicate that new segments are available. To Druid, there is no difference between segments generated by the real-time logic with those generated by batch processing, and Druid will proceed to load the batch generated segments.

Our ingestion model is hopefully more clear at this point. We use the streaming data pipeline described in Section4.1 to deliver immediate insights on events as they are occurring, and the batch data pipeline described in this section to provide the accurate copy of the data. The batch process typically runs much less frequently than the real-time process, and may run many hours or even days after raw events have been delivered. The wait is necessary for severely delayed events, and to ensure that the raw data is indeed complete.

Segments generated by the batch process are versioned by the start time of the process. Hence, segments created by batch processing will have a version identifier that is greater than segments created by real-time processing. When these batch created segments are loaded in the cluster, they atomically replace segments created by real-time processing for their processed interval. Hence, soon after batch processing completes, Druid switches to querying for the accurate copy of the data.

4.3 Starfire

To avoid writing the same processing logic on both Hadoop and Samza, we created a library called Starfire to help generate workflows on both batch and stream processing frameworks. Starfire has a streaming model of computation at its heart, even when running in batch mode. It is designed to never need to load up all your data at once, in any mode of operation, but it offers operators that do need to work across multiple data points, like "groupBy" and "join". Since these operators cannot run across the entire data set, Starfire runs them using windows.

Starfire programs ask for a particular window size (measured in time, like 15 minutes or two hours) that particular drivers must provide. The Hadoop driver provides a window size by loading up data surrounding the data that you are actually interested in. The Samza driver does it by buffering data in a key/value store for a period of time. Starfire supports using different window sizes from driver to driver, which can be useful if you are running a combination batch/real-time architecture. We hope to explore Starfire more in future literature.

5. THE DELIVERY LAYER

In our stack, events are delivered over HTTP to Kafka. Events are transmitted via POST requests to a receiver that acts as a front for a Kafka producer. Kafka is a distributed messaging system with a publish and subscribe model. At a high level, Kafka maintains events or messages in categories called topics. A distributed Kafka cluster consists of numerous brokers, which store messages in a replicated commit log. Kafka consumers subscribe to topics and process feeds of published messages.

Kafka provides isolation of functionality in terms with producers of data and consumers of data. The publish/subscribe model works well for our use case as multiple consumers can subscribe to the same topic and process the same set of events. We have two primary Kafka consumers. The first is a Samza job that reads messages from Kafka for stream processing as described in Section 4.1. The second consumer read messages from Kafka and stores them in a distributed file system, similar to Camus []. This file system is the same as the one used for Druid's deep storage, and also acts as a backup for raw events. Topics in Kafka map directly to pipelines in Samza, and pipelines in Samza map directly to data sources in Druid. The purpose of storing raw events in deep storage is so that we can run batch processing jobs over them at any given time. For example, our stream processing layer may choose to not include certain columns when it first processes a few pipeline. If clients demand these columns be included in the future, we can reprocess the raw data to generate new Druid segments.

Kafka is the single point of delivery for events entering our system, and must have the highest availability. We replicate our Kafka producers across multiple datacenters. In the event that Kafka brokers and consumers become unresponsive, as long as our HTTP endpoints are still available, we can buffer events on the producer side while recovering the system. Similarity, if our processing and serving layers completely fail, we can recover by replaying events from Kafka.

6. PERFORMANCE

Druid runs in production at several organizations, and to briefly demonstrate its performance, we have chosen to share some real world numbers for the main production cluster running at Metamarkets in early 2015. For comparison with other databases we also include results from synthetic workloads on TPC-H data.

6.1 Query Performance in Production

Druid query performance can vary signficantly depending on the query being issued. For example, sorting the values of a high cardinality dimension based on a given metric is much more expensive than a simple count over a time range. To showcase the average query latencies in a production Druid cluster, we selected 8 of our most queried data sources, described in Table 3.

Approximately 30% of queries are standard aggregates involving different types of metrics and filters, 60% of queries are ordered group bys over one or more dimensions with aggregates, and 10% of queries are search queries and metadata retrieval queries. The number of columns scanned in aggregate queries roughly follows an exponential distribution. Queries involving a single column are very frequent, and queries involving all columns are very rare.

- The results are from a "hot" tier in our production cluster. There were approximately 50 data sources in the tier and several hundred users issuing queries.

Data Source	Dimensions	Metrics
a	25	21
b	30	26
c	71	35
d	60	19
e	29	8
f	30	16
g	26	18
h	78	14

Table 3: Characteristics of production data sources.

- There was approximately 10.5TB of RAM available in the "hot" tier and approximately 10TB of segments loaded. Collectively, there are about 50 billion Druid rows in this tier. Results for every data source are not shown.

- The hot tier uses Intel® Xeon® E5-2670 processors and consists of 1302 processing threads and 672 total cores (hyperthreaded).

- A memory-mapped storage engine was used (the machine was configured to memory map the data instead of loading it into the Java heap.)

Query latencies are shown in Figure 4 and the queries per minute are shown in Figure 5. Across all the various data sources, average query latency is approximately 550 milliseconds, with 90% of queries returning in less than 1 second, 95% in under 2 seconds, and 99% of queries returning in less than 10 seconds. Occasionally we observe spikes in latency, as observed on February 19, where network issues on the Memcached instances were compounded by very high query load on one of our largest data sources.

6.2 Query Benchmarks on TPC-H Data

We also present Druid benchmarks on TPC-H data. Most TPC-H queries do not directly apply to Druid, so we selected queries more typical of Druid's workload to demonstrate query performance.

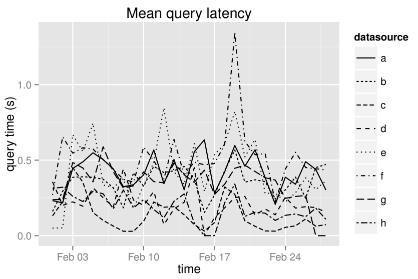
Our Druid setup used Amazon EC2 `m3.2xlarge` instance types (Intel® Xeon® E5-2680 v2 @ 2.80GHz) for historical nodes and `c3.2xlarge` instances (Intel® Xeon® E5-2670 v2 @ 2.50GHz) for broker nodes. Our MySQL setup was an Amazon RDS instance that ran on the same `m3.2xlarge` instance type.

The results for the 1 GB TPC-H data set are shown in Figure 6 and the results of the 100 GB data set are shown in Figure 7. We benchmarked Druid's scan rate at 53,539,211 rows/second/core for `select count(*)` equivalent query over a given time interval and 36,246,530 rows/second/core for a `select sum(float)` type query.

Finally, we present our results of scaling Druid to meet increasing data volumes with the TPC-H 100 GB data set. We observe that when we increased the number of cores from 8 to 48, not all types of queries achieve linear scaling, but the simpler aggregation queries do, as shown in Figure 8.

he increase in speed of a parallel computing system is often limited by the time needed for the sequential operations of the system. In this case, queries requiring a substantial amount of work at the broker level do not parallelize as well.

6.3 Data Ingestion Performance



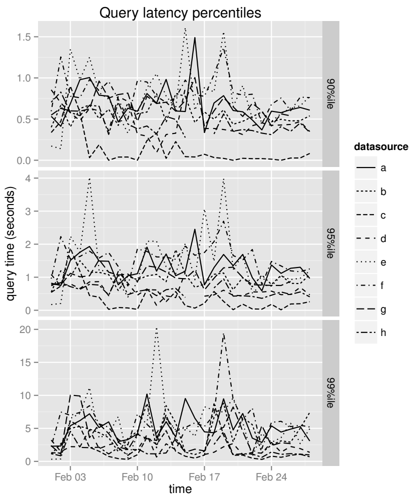


Figure 4: Query latencies of production data sources.

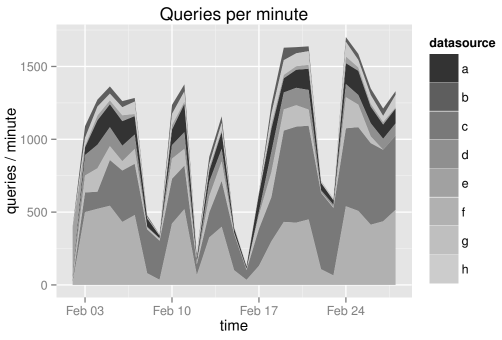


Figure 5: Queries per minute of production data sources.

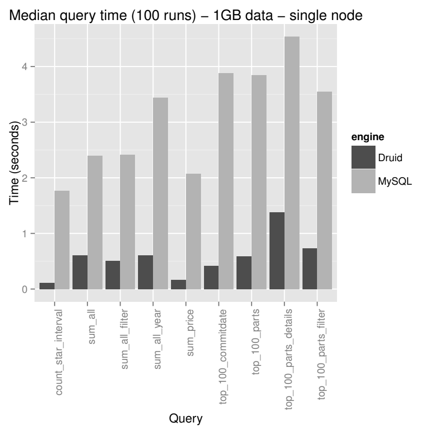


Figure 6: Druid benchmarks – 1GB TPC-H data.

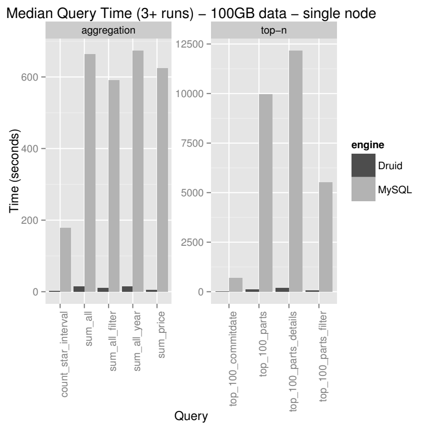


Figure 7: Druid benchmarks – 100GB TPC-H data.

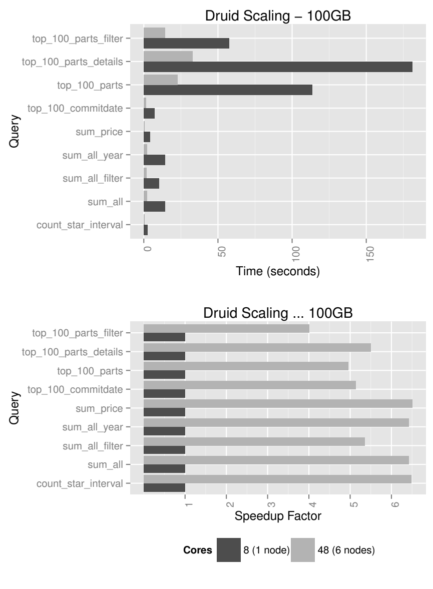


Figure 8: Druid scaling benchmarks – 100GB TPC-H data.

To showcase Druid's data ingestion latency, we selected several production datasources of varying dimensions, metrics, and event volumes. Our production ingestion setup consists of 6 nodes, totalling 360GB of RAM and 96 cores (12 x Intel®Xeon®E5-2670).

Note that in this setup, several other data sources were being ingested and many other Druid related ingestion tasks were running concurrently on the machines.

Druid's data ingestion latency is heavily dependent on the complexity of the data set being ingested. The data complexity is determined by the number of dimensions in each event, the number of metrics in each event, and the types of aggregations we want to perform on those metrics. With the most basic data set (one that only has a timestamp column), our setup can ingest data at a rate of 800,000 events/second/core, which is really just a measurement of how fast we can deserialize events. Real world data sets are never this simple. Table **??** shows a selection of data sources and their characteristics.

7. PRODUCTION EXPERIENCES

7.1 Experiences with Druid

7.1.1 Query Patterns

Druid is used for exploratory analytics and reporting, which are two very distinct use cases. Exploratory analytic workflows uncover discoveries by progressively narrowing down a view of data until an interesting insight is made. Users tend to explore short intervals of recent data. In the reporting use case, users query for much longer data intervals, and the volume of queries is generally much less. The insights that users are looking for are often pre-determined.

7.1.2 Multitenancy

Expensive concurrent queries can be problematic in a multitenant environment. Queries for large data sources may end up hitting every historical node in a cluster and consume all cluster resources. Smaller, cheaper queries may be blocked from executing in such cases. We introduced query prioritization to address these issues. Each historical node is able to prioritize which segments it needs to scan. Proper query planning is critical for production workloads. Thankfully, queries for a significant amount of data tend to be for reporting use cases and can be de-prioritized. Users do not expect the same level of interactivity in this use case as they do when they are exploring data.

7.1.3 Node Failures

Single node failures are common in distributed environments, but many nodes failing at once are not. If historical nodes completely fail and do not recover, their segments need to be reassigned, which means we need excess cluster capacity to load this data. The amount of additional capacity to have at any time contributes to the cost of running a cluster. From our experiences, it is extremely rare to see more than 2 nodes completely fail at once and hence, we leave enough capacity in our cluster to completely reassign the data from 2 historical nodes.

7.2 Experiences with Ingestion

7.2.1 Multitenancy

Before moving our streaming pipeline to Samza, we experimented with other stream processors. One of the biggest pains we felt was multi-tenancy. Multiple pipelines may contend for resources, and it is often unclear how various jobs impact one another when running in the same environment. Given that each of our pipelines is composed of different tasks, Samza was able to provide per task resource isolation, which was far easier to manage than per application resource isolation.

7.2.2 Autoscaling

Autoscaling our cluster to adjust for changes in load has remained a difficult problem. Production load is not constant, and different peaks can occur at vastly different times during a day. We've elected to focus on the problem of gradually increasing load, instead dealing with immediate spikes or dips in load. As load increases, we add new resources but set a configurable limit on how fast they can be added. We scale down our cluster very slowly, excess capacity may remain for several hours before the system decides they are no longer necessary.

7.3 Operational Monitoring

Proper monitoring is critical to run a large scale distributed cluster, especially with many different technologies. Each Druid node is designed to periodically emit a set of operational metrics. These metrics may include system level data such as CPU usage, available memory, and disk capacity, JVM statistics such as garbage collection time, and heap usage, or node specific metrics such as segment scan time, cache hit rates, and data ingestion latencies. Druid also emits per query metrics so we can examine why a particular query may be slow. We've also added functionality to periodically emit metrics from Samza, Kafka, and Hadoop. We emit metrics from our production RADStack and load them into a dedicated metrics RADstack. The metrics cluster is used to explore the performance and stability of the production cluster. This dedicated metrics cluster has allowed us to find numerous production problems, such as gradual query speed degradations, less than optimally tuned hardware, and various other system bottlenecks. We also use a metrics cluster to analyze what queries are made in production and what aspects of the data users are most interested in.

8. RELATED WORK

8.1 Hybrid Batch/Streaming Workflows

8.1.1 Summingbird

Summingbird[] is a high-level dataflow language for streaming and batch processing. Summingbird enables counters on top of streams, and processes data for delivery to key/value stores. Summingbird can run on top of data processors such as Storm[] and Hadoop. The RADStack also offers a language for writing data processing jobs with Starfire. These jobs do not involve computation and focus entirely on data processing. Starfire enables more complex operations such as streaming joins. Moreover, the RADStack leaves all queries and aggregations to the serving layer, letting each layer of the stack focus on what it is best at.

8.1.2 Spark Ecosystem

Spark[] is a cluster computing framework optimized for iterative workflows. Spark Streaming[] is a separate project that converts sequences of tuples into immutable micro-batches. Each micro-batch can be processed using the underlying Spark framework. Spark SQL is a query optimization layer that can sit on top of Spark and issue SQL queries, along with Spark's native analytic queries. Druid's approach to querying is quite different and Druid insteads builds immutable indexed data structures optimized for low latency OLAP queries, and does not leverage lineage[] in computations. The RADStack can theoretically be composed of Spark and Spark Streaming for processing, Kafka for event delivery, and Druid to serve queries.

8.2 Druid and Other Data Stores

Although Druid builds on many of the same principles as other distributed columnar data stores[9], many of these data stores are designed to be more generic key-value stores[14] and do not support computation directly in the storage layer. There are also other data stores designed for some of the same data warehousing issues that Druid is meant to solve. These systems include in-memory databases such as SAP's HANA[8] and VoltDB[23]. These data stores lack Druid's low latency ingestion characteristics. Druid also has native analytical features baked in, similar to ParAccel[18], however, Druid allows system wide rolling software updates with no downtime.

Druid is similar to C-Store[20] and LazyBase[4] in that it has two subsystems, a read-optimized subsystem in the historical nodes and a write-optimized subsystem in real-time nodes. Real-time nodes are designed to ingest a high volume of append heavy data, and do not support data updates. Unlike the two aforementioned systems, Druid is meant for OLAP transactions and not OLTP transactions. Druid's low latency data ingestion features share some similarities with Trident/Storm[16] and Spark Streaming[24], however, both systems are focused on stream processing whereas Druid is focused on ingestion and aggregation. Stream processors are great complements to Druid as a means of pre-processing the data before the data enters Druid.

There are a class of systems that specialize in queries on top of cluster computing frameworks. Shark[7] is such a system for queries on top of Spark, and Cloudera's Impala[5] is another system focused on optimizing query performance on top of HDFS. Druid historical nodes download data locally and only work with native Druid indexes. We believe this setup allows for faster query latencies. Druid leverages a unique combination of algorithms in its architecture. Although we believe no other data store has the same set of functionality as Druid, some of Druid's optimization techniques such as using inverted indices to perform fast filters are also used in other data stores[15].

9. CONCLUSIONS AND FUTURE WORK

In this paper we presented the RADStack, a collection of complementary technologies that can be used together to power interactive analytic applications. The key pieces of the stack are Kafka, Samza, Hadoop, and Druid. Druid is designed for exploratory analytics and is optimized for low latency data exploration, aggregation, and ingestion, and is well suited for OLAP workflows. Samza and Hadoop complement Druid and add data processing functionality, and Kafka solves the event delivery problem.

We believe that although our solution currently requires batch processing, in later iterations of this work, that piece of the stack may not be necessary. As open source technologies mature, the existing problems around exactly-once processing will eventually be solved. The Druid, Samza and Kafka communities are actively working on exactly once, lossless processing for their respective systems, and in the near future, the same guarantees that the RADStack provides right now will be available using only these technologies.

10. ACKNOWLEDGMENTS

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