

From Zero to Hero with Apache Kudu

BOSS 2019

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Follow along with the walkthroughs!

https://bit.ly/2ZsR6m6

Who am I?

Andrew Wong

- Software engineer at Cloudera (<u>awong@cloudera.com</u>)
- Apache Kudu PMC Member

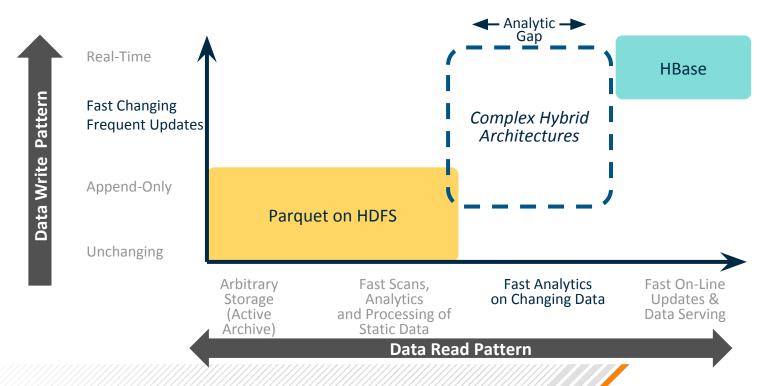
Some Kudu things I have worked on:

- Scan optimizations
- Disk failure mitigation
- Integration with Hive Metastore (external catalog)
- Fine-grained authorization



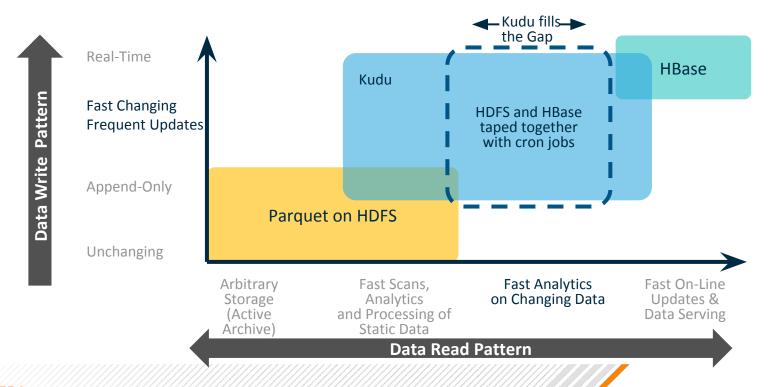
Traditional big data storage leaves a gap

Use cases fall between HDFS and HBase were difficult to manage

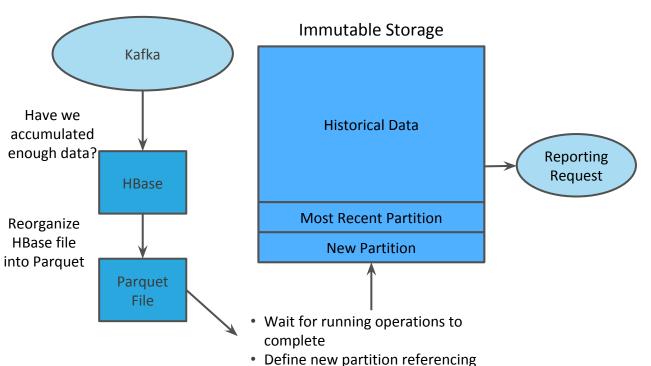


Traditional big data storage leaves a gap

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"Traditional" real-time analytics

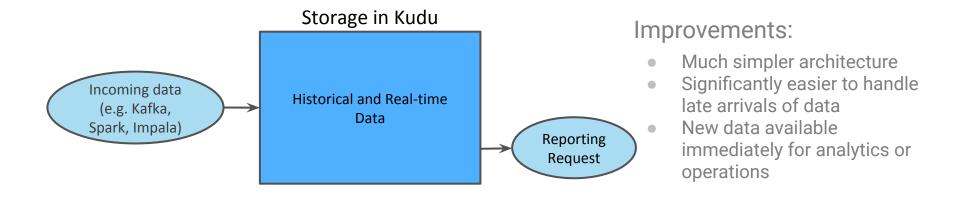


the newly written Parquet file

Considerations:

- How do I handle failure during this process?
- How often do I reorganize data streaming in into a format appropriate for reporting?
- When reporting, how do I see data that has not yet been reorganized?
- How do I ensure that important jobs aren't interrupted by maintenance?

Real-time analytics with Kudu



Mutable data storage engine, designed for analytics on real-time data

MUTABLE

STORAGE

ANALYTICS

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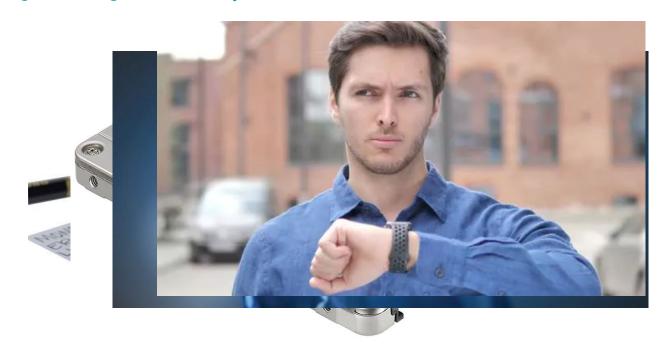


Mutable data storage engine, designed for analytics on real-time data

MUTABLE

STORAGE

ANALYTICS



"Big deal... Aren't there a ton of big data systems out there?"

Yes there are.

- Open source
 - Parquet on HDFS, object storage
 - HBase/Cassandra
 - TiDB with TiFlash
 - o etc.
- Proprietary
 - Vertica, Teradata, SAP
 - Spanner
 - Redshift



Why else did we build Kudu?

Changing hardware landscape

- Spinning disks --> solid state storage
 - NAND flash: up to 450k read, 250k write IOPS, ~2GB/s read and ~1.5GB/s write throughput, at under \$1/GB
 - PMEM: order of magnitude faster than NAND, cheaper than RAM
- RAM is getting cheaper and more abundant
 - 128 --> 256 --> 512 GB over the last few years

Takeaway: The next bottleneck is CPU, and current storage systems weren't designed with CPU efficiency in mind.

Scalable and fast tabular storage

Scalable

- Production clusters with hundreds of nodes
- On the order of hundreds of TBs to low PBs

Fast

- Written primarily in C++
- Millions of write operations per second across cluster
- Multiple GB/s read throughput per node

Tabular

Strict schema, finite column count, no BLOBs



And we've got some friends!

Apache and CNCF













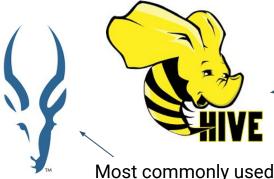






And we've got some friends!

Apache and CNCF



















Dev only







The rest of the Ecosystem isn't that scary

Somewhat clear lines between roles







Ingest:

NiFi, Spark Streaming, Flink, Kafka, Flume

Storage:

- Kudu
- Previously HBase, HDFS, and a lot of cron jobs

Querying:

Impala, Hive, Spark SQL







From Zero to Hero with Apache Kudu

Agenda

Start with the basics:

- Introduction to Kudu's data model
- Distributed architecture

Jump into more complex things:

- Schema design exercises
- Partitioning in Kudu

Deploy a small "big data" pipeline:

Spark, Nifi

From Zero to Hero with Apache Kudu

If you can

- Pull from GitHub:
 - o apache/kudu:master
- Pull from DockerHub:
 - o apache/kudu:latest
- brew install apache-spark

A primer on Kudu concepts

What is "data" to Kudu?

Table: prominent abstraction for users -- a set of uniquely identifiable rows **Schema:** describes the columns and ordering of the rows of a table

Subset of columns defined as "primary key"

Partition schema: describes the partitions of a table

Subset of primary key defined as "partition key"

Tablet: partition of a table; the logical unit of replication and parallelization

- Underlying data stored in sorted order by primary key
- Tablet replicas are dispersed among servers in a cluster

Very much LSM-inspired

Write-ahead log: as writes come in, they are written in fast, row-oriented storage

Mem-Rowset: as writes are written to the WAL, they are also applied to an in-memory, row-oriented B-Tree

Periodic flushes: as the mem-rowset grows large, there are periodic flushes to free up memory and transition the mem-rowset to a disk-rowset

Many Disk-Rowsets: represented as an interval tree for lookups

Wait what is "LSM"? You said we're starting from zero!

- LSM: Log Structured Merge (Cassandra, HBase, etc)
 - Inserts and updates all go to an in-memory map (MemStore) and later flush to on-disk files (HFile/SSTable)
 - Reads perform an on-the-fly merge of all on-disk HFiles
- Kudu
 - Shares some traits (memstores, compactions)
 - More complex.
 - Slower writes in exchange for faster reads (especially scans)

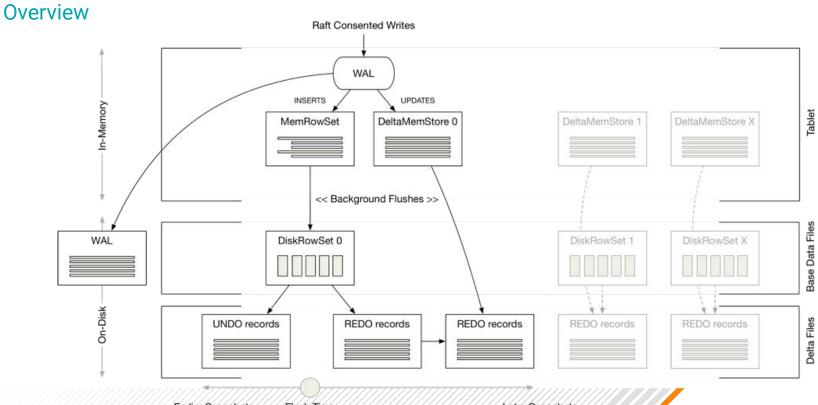
And more!

B-Tree index per rowset to enable search on a primary key **Bloom filter** per rowset to enable lookups for deduplication of rows **CFiles** the actual columnar data, in primary key order

Deltas (updates and deletes)

- In-memory delta store per rowset
- On-disk delta stores per rowset
- New updates are represented as REDO records, periodically flushed to UNDO records to avoid REDO traversal





Maintenance Manager

Always be flushing and compacting!

- The maintenance manager handles background tasks
 - Flushing the MRS or DMS to disk
 - Compactions
 - WAL GC
- A maintenance manager thread decides what task to perform using a cost-based optimization model
 - Prefers flushing when the server is under memory pressure



Main roles in Kudu

Master: a server that hosts Kudu system metadata and catalog information

Tablet server: a server that hosts tablet replicas

Client: an application that inserts to or reads from Kudu

- Tooling
- C++ application
- Java
- Python
- Spark
- Impala
- ...

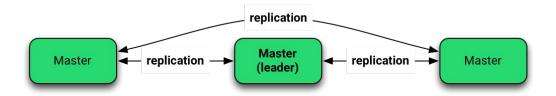


Let's walk through deploying Kudu!

https://bit.ly/2ZsR6m6

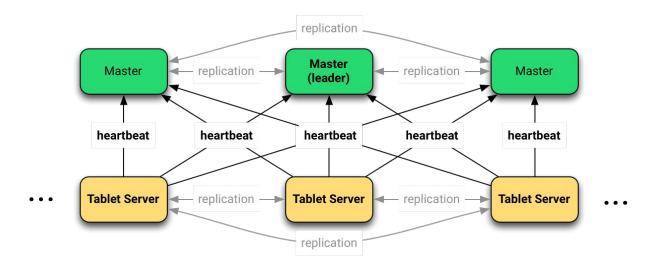
Explore a single node deployment of Kudu

Replication, replication!

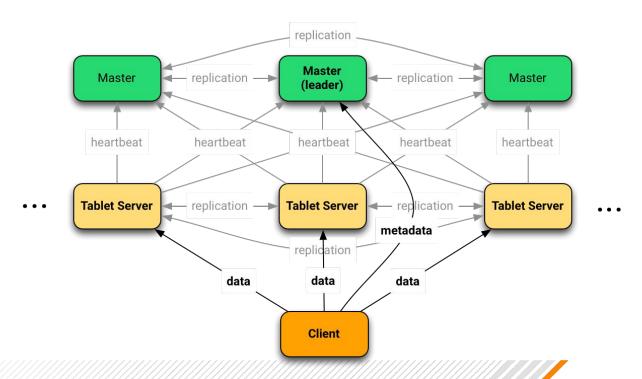




Replication, replication!



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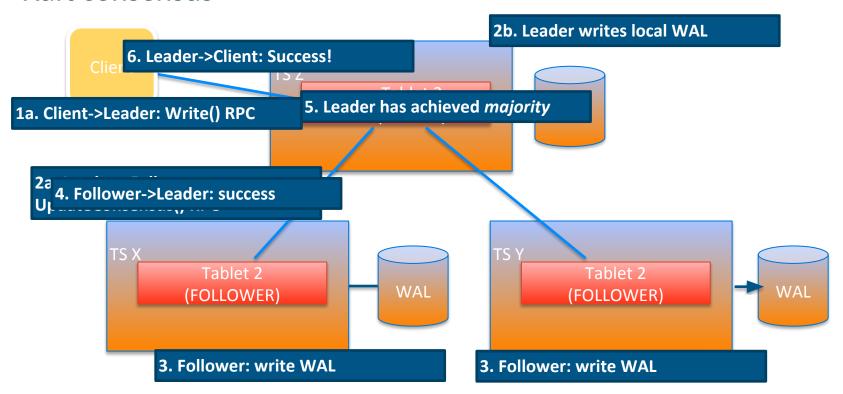
Raft consensus

Consensus protocol to replicate data

- Leaders constantly heartbeating to followers
- Leader elections triggered when a follower doesn't hear back from leader
- Write operations go to leader first and are replicated to followers



Raft consensus



Dealing with node failures

Wait long enough, and Kudu heals itself!

- If a Raft leader notices that it hasn't heard from one of its replicas in a while, it will try to create a new replica
- Physical copy of leader sent to new replica
- Old replica is removed from Raft configuration



Master details

- All table and tablet metadata is stored in a single tablet
- Like any other tablet, the metadata tablet is replicated via Raft
- Master is effectively a tablet server for this one tablet
- Failure handling
 - Transient failures are handled transparently
 - Permanent failures require operator intervention



Balance and Skew

Tablet replica placement controlled by the master based on its view of the world

- Placement uses "Power of Two Choices" algorithm to even out replica count across cluster
 - Select two tablet servers, pick the one with fewer tablet replicas
- Rebalancer tool can be run to redistribute replicas in case of skew



Cluster health

kudu cluster ksck <masters>

When operating Kudu, this is your lifeline!

Tells you:

- What servers exist
- What tables and tablets exist
- What tablet are under-replicated and recovering
- What the skew on the cluster is like
- What non-default flags are set

Client abstractions

Sessions:

In-memory write buffers, eventually get "flushed" to the servers

Scanners:

Fetches rows one batch at a time

Client abstractions (writes)

```
KuduTable table = client.openTable("metrics");
KuduSession session = client.newSession();
Insert ins = table.newInsert();
ins.getRow().addString("host", "foo.example.com");
ins.getRow().addString("metric", "load-avg.1sec");
ins.getRow().addDouble("value", 0.05);
session.apply(ins);
session.flush();
```

Client abstractions (scans)

```
KuduScanner scanner = client.newScannerBuilder(table)
  .setProjectedColumnNames(Lists.of("value"))
  .build();
while (scanner.hasMoreRows()) {
  RowResultIterator batch = scanner.nextRows();
  while (batch.hasNext()) {
    RowResult result = batch.next();
    System.out.println(result.getDouble("value"));
```

Client abstractions (scans, but with predicates!)

```
KuduScanner scanner = client.newScannerBuilder(table)
  .addPredicate(KuduPredicate.newComparisonPredicate(
     table.getSchema().getColumn("timestamp"),
     ComparisonOp.GREATER,
     System.currentTimeMillis() / 1000 + 60))
  .build();
```

Note: Kudu can evaluate simple predicates, but no aggregations, complex expressions, UDFs, etc.

Client cluster interaction

Master

- Tablet metadata fetched from the master, including locations and partitioning info
- Tablets are "pruned" via partitioning info so only the appropriate tablets are scanned

Tablet servers

- Requests sent to tablet servers
- Rejected if appropriate



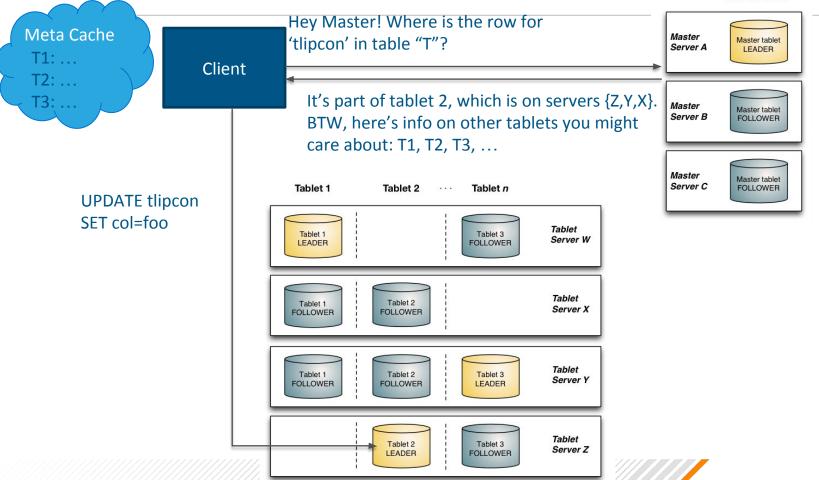
Client consistency models

Choose the one which fits your workload!

- READ_LATEST (default mode)
 - Read committed state immediately
- READ_AT_SNAPSHOT
 - Consistent and repeatable
 - This allows strict-serializable semantics for reads and writes
- READ_YOUR_WRITES (Kudu 1.7 and up)
 - Ensures all previously read and written values are read
 - Not repeatable



Master tablet



Continuing the walkthrough!

https://bit.ly/2ZsR6m6

Explore a multinode deployment

Time Series

To demonstrate advanced table partitioning techniques, we are going to think through a table for time series storage of machine metrics.

Time Series

Series	Time	Value
us-east.appserver01.loadavg.1min	2016-05-09T15:14:30Z	0.44
us-east.appserver01.loadavg.1min	2016-05-09T15:14:40Z	0.53
us-west.dbserver03.rss	2016-05-09T15:14:30Z	1572864
us-west.dbserver03.rss	2016-05-09T15:15:00Z	2097152

Time Series — Design Criteria

- Insert Performance (throughput & latency)
- Read Performance (throughput & latency)
 - What kind of queries are you doing?
 - Look at all metrics at a specific time
 - Look at one metric across a long span of time



Time Series — Common Patterns

- Datapoints are inserted in time order across all series
- Reads specify a series and a time range, containing hundreds to many thousands of datapoints

```
SELECT time, value FROM timeseries
WHERE series = "us-west.dbserver03.rss"
AND time >= 2016-05-08T00:00:00;
```

Reminder: Partitioning vs Indexing

- Partitioning: how datapoints are distributed among partitions
 - Kudu: tablet
 - HBase: region
 - Cassandra: VNode
- Indexing: how data within a single partition is sorted

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(us-east.appserver01.loadavg, 2016-05-09T15:14:00Z) (us-east.appserver01.loadavg, 2016-05-09T15:15:00Z) (us-west.dbserver03.rss, 2016-05-09T15:14:30Z) (us-west.dbserver03.rss, 2016-05-09T15:14:30Z)

(series, time)

(2016-05-09T15:14:00Z, us-east.appserver01.loadavg) (2016-05-09T15:14:30Z, us-west.dbserver03.rss) (2016-05-09T15:15:00Z, us-east.appserver01.loadavg) (2016-05-09T15:14:30Z, us-west.dbserver03.rss)

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```

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(series, time) (time, series) SELECT * WHERE series = 'us-east.appserver01.loadavg';

Partitioning

- Kudu has flexible policies for distributing data among partitions
 - Hash partitioning is built in, and can be combined with range partitioning
- Goal: acceptable distribution of data across tablets at any given time
- Goal: allow expected scans to prune tablets
- Indexing is independent of partitioning!!!



Partitioning — By Time Range

time

Partition 1

start: 2016-05-07T00:00:00Z end: 2016-05-08T00:00:00Z

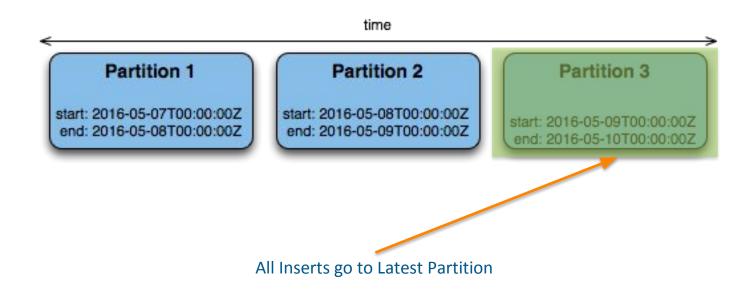
Partition 2

start: 2016-05-08T00:00:00Z end: 2016-05-09T00:00:00Z

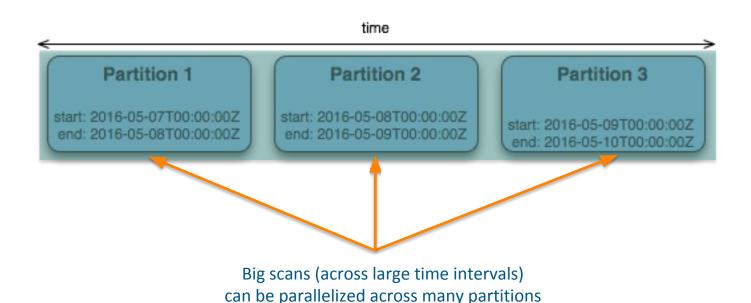
Partition 3

start: 2016-05-09T00:00:00Z end: 2016-05-10T00:00:00Z

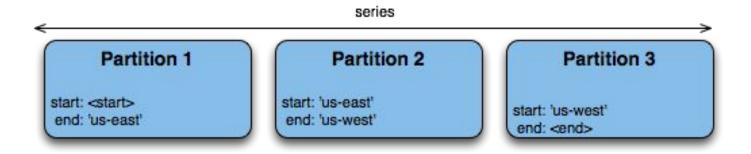
Partitioning — By Time Range (inserts)



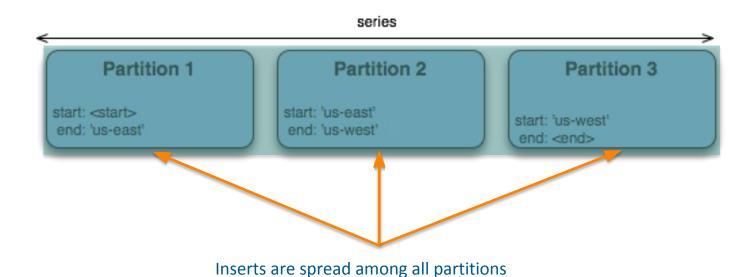
Partitioning — By Time Range (scans)



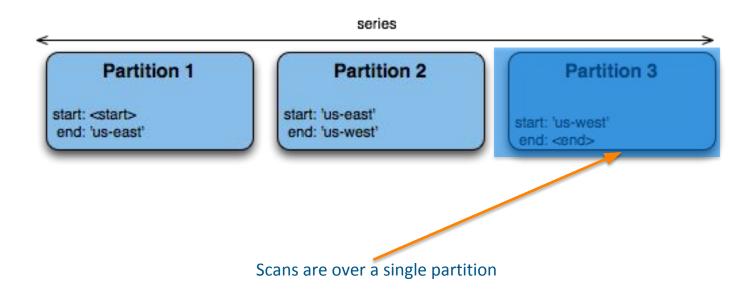
Partitioning — By Series Range



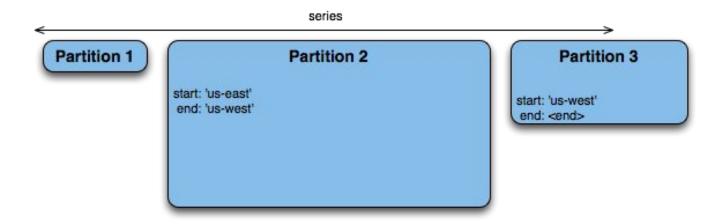
Partitioning — By Series Range (inserts)



Partitioning — By Series Range (scans)

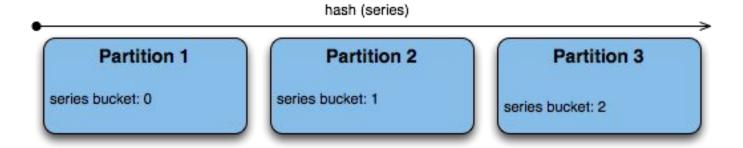


Partitioning — By Series Range

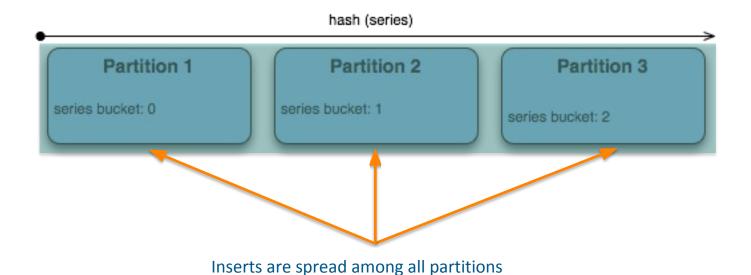


Partitions can become unbalanced, resulting in hot spotting

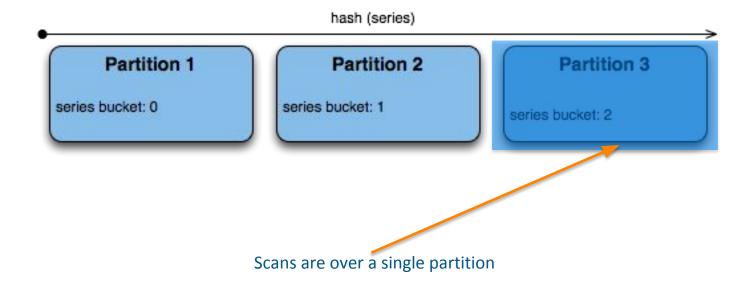
Partitioning — By Series Hash



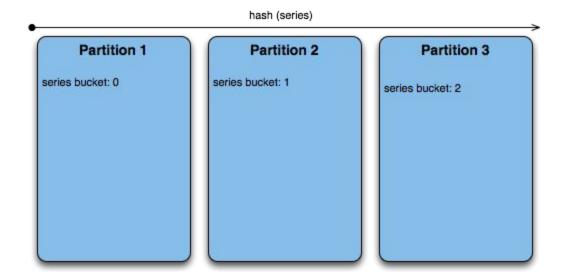
Partitioning — By Series Hash (inserts)



Partitioning — By Series Hash (scans)

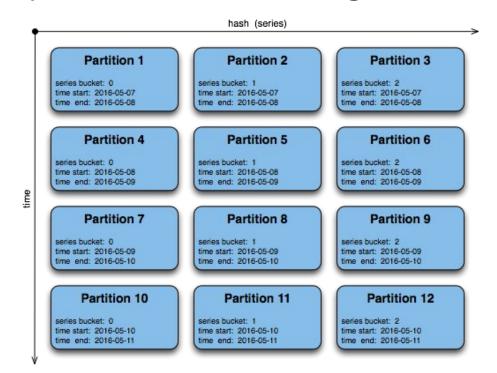


Partitioning — By Series Hash

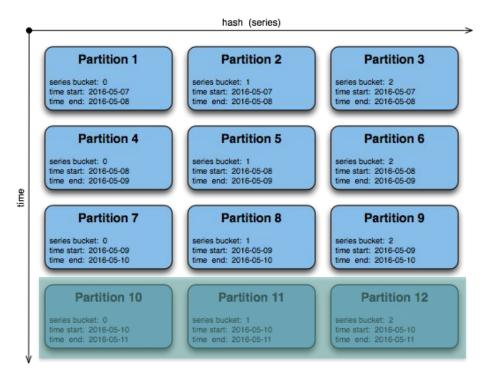


Partitions grow overtime, eventually becoming too big for a single server

Partitioning — By Series Hash + Time Range

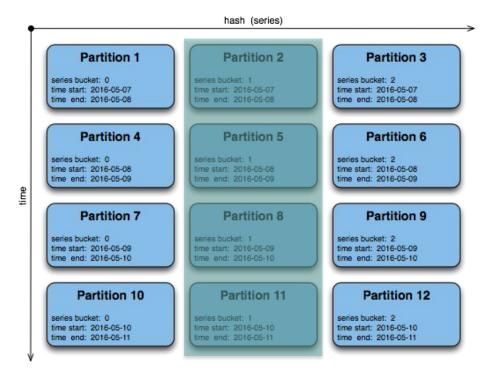


Partitioning — By Series Hash + Time Range (inserts)



Inserts are spread among all partitions in the latest time range

Partitioning — By Series Hash + Time Range (scans)



Big scans (across large time intervals) can be parallelized across partitions

Spark SQL and Nifi walkthrough

- Deploy some Spark
- Deploy some Nifi
- ???
- Profit



Spark DataSource optimizations

- Column projection and predicate pushdown
 - Only read the referenced columns
 - Convert 'WHERE' clauses into Kudu predicates
 - Kudu predicates automatically convert to primary key scans, etc



Spark DataSource optimizations

Predicate pushdown

Spark DataSource optimizations

Partition pruning

```
scala> df.where("host like 'foo%'").rdd.partitions.length
res1: Int = 20
scala> df.where("host = 'foo'").rdd.partitions.length
res2: Int = 1
```

Writing via Spark

```
// Use KuduContext to create, delete, or write to Kudu tables
val kuduContext = new KuduContext("kudu-master:7051,kudu-master:7151,kudu-master:7251")

// Create a new Kudu table from a dataframe schema
// NB: No rows from the dataframe are inserted into the table
kuduContext.createTable("test_table", df.schema, Seq("key"), new CreateTableOptions().setNumReplicas(1))

// Insert, delete, upsert, or update data
kuduContext.insertRows(df, "test_table")
kuduContext.deleteRows(sqlContext.sql("select id from kudu_table where id >= 5"), "kudu_table")
kuduContext.upsertRows(df, "test_table")
kuduContext.updateRows(df.select("id", $"count" + 1, "test_table")
```

Spark SQL and Nifi walkthrough

https://bit.ly/2ZsR6m6

- Deploy some Spark
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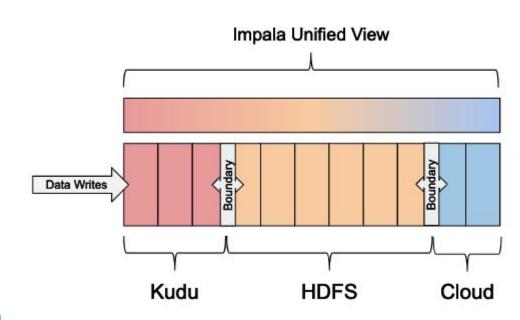
Interesting pattern: Hierarchical storage

Return of the Lambda? (but longer time scale)

- Use Impala to periodically (e.g. every month) move data from Kudu into cold storage
- Query both hot Kudu data and colder HDFS and Cloud data with a view
- Simpler primitives than before

Excellent blog post:

https://kudu.apache.org/2019/03/05/transparent-hierarchicalstorage-management-with-apache-kudu-and-impala.html



Thank you!

Twitter: @ApacheKudu

Slack: https://getkudu-slack.herokuapp.com/

Website: kudu.apache.org

Questions?

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