Fast Scans on Key-Value Stores

By David Shen and Beatrice Tanaga

About the Authors

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Introduction to KVS

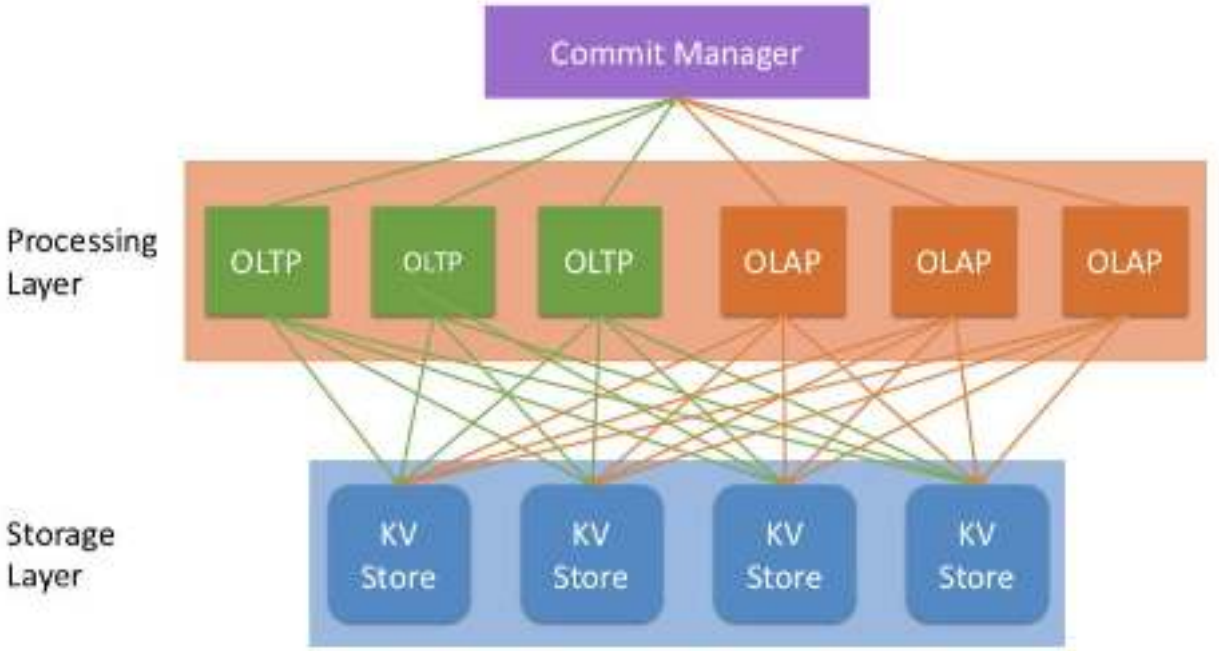
What is a Key-Value Store?

- A type of **storage engine** that stores values indexed by a key.

RamCloud

State of the Art KVS

- Processing layer is responsible for **synchronization**
- Snapshot Isolation is used for synchronization in the commit manager.
- A form of Multi-Version Concurrency Control (a way for the system to provide concurrent accesses to the DB)

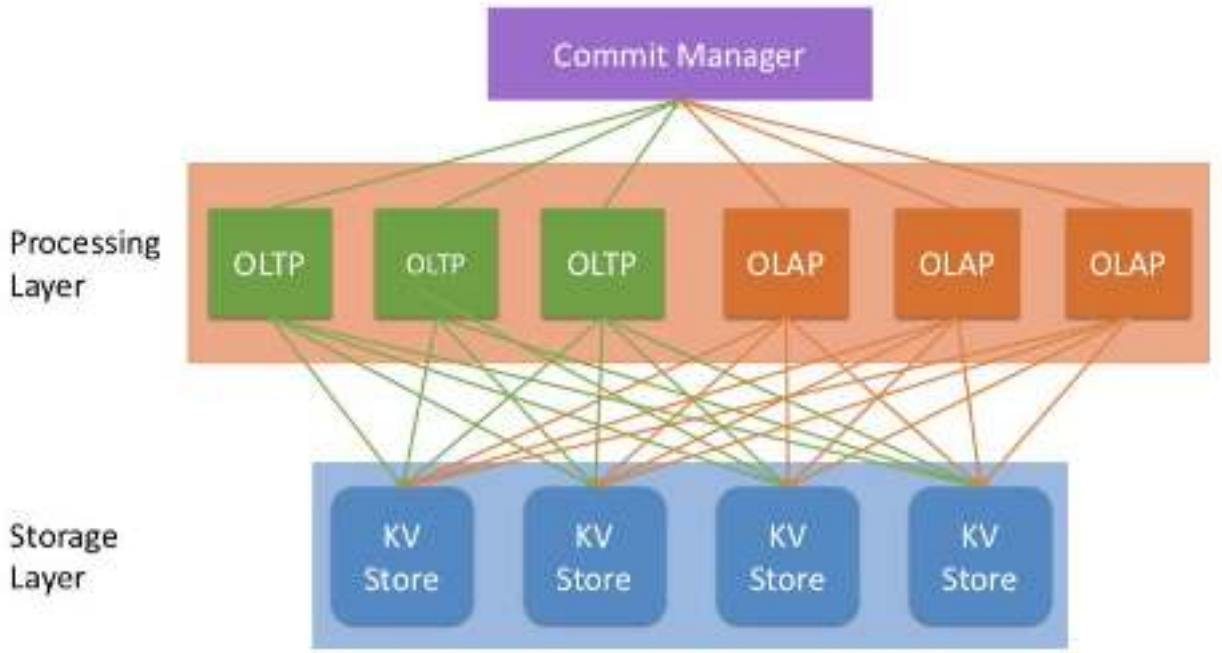


SQL-over-NoSQL Architecture

Advantages of this Design

- Elasticity
- Scalability
- Sustains high throughput for get/put (OLTP) workloads
- Can decouple the storage component and allow it to be part of a completely isolated offering (eg. DynamoDB as part of AWS).

Any downsides?



SQL-over-NoSQL Architecture

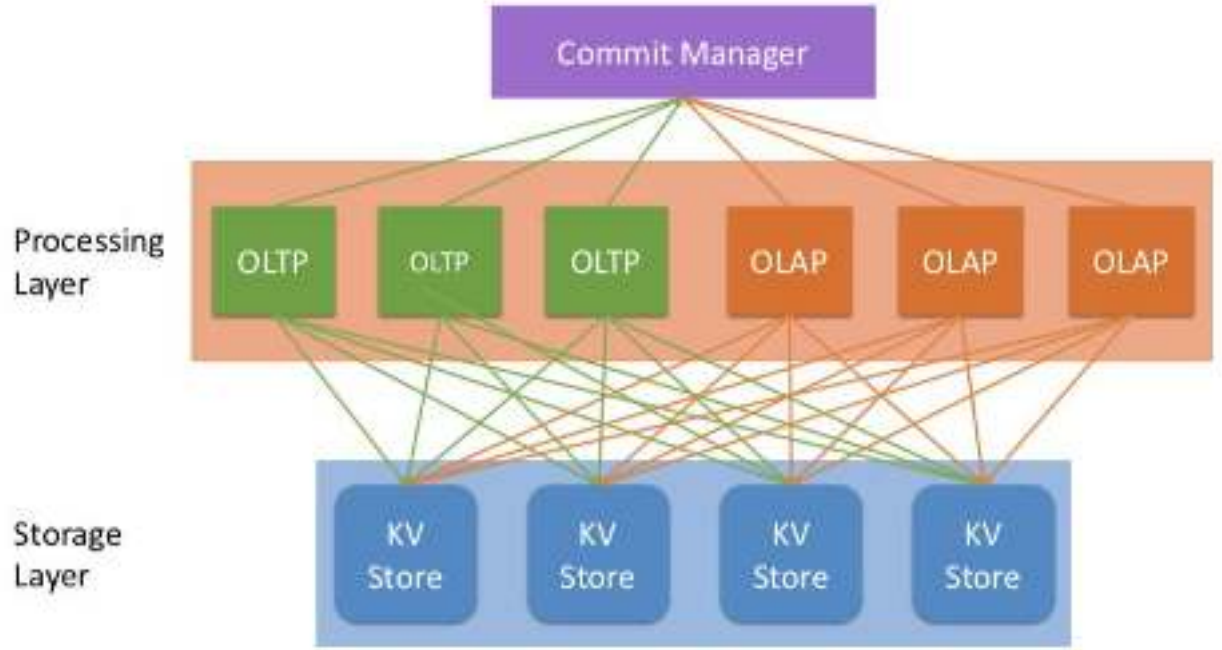
Downsides

Issues:

- Access patterns of OLTP and OLAP workloads are different
- OLAP workloads requires reading large, or at times all, portions of the data
- Conflict of interest: Get/Put workloads require sparse indexes, while scans require spatial locality.

Key-Value Store	Scan Time
Cassandra [28]	19 minutes
RAMCloud [34]	46 seconds
HBase [20]	36 seconds
RocksDB [16]	2.4 seconds
Kudu [19]	1.8 seconds
MemSQL [31]	780 milliseconds
TellStore-Row	*197 milliseconds*
TellStore-Log	*133 milliseconds*
TellStore-Column	*84 milliseconds*

```
SELECT max(B) FROM main_table
```


Commit Manager
Processing Layer
OLTP
OLTP
OLTP
OLAP
OLAP
OLAP
Storage Layer
KV Store
KV Store
KV Store
KV Store

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SQL-over-NoSQL Architecture cont.

- What are the distributed KVS requirements to efficiently implement the SQL-over-NoSQL architecture?

1. Scans
2. Versioning
3. Batching and Asynchronous Communication

SQL-over-NoSQL Architecture cont.

- What are the distributed KVS requirements to efficiently implement the SQL-over-NoSQL architecture?

1. Scans
   - KVS must be able to support efficient scan operations in addition to get/put requests
   - Selections, projections and simple aggregates should be supported
     - This allows only the relevant data to be fetched from storage layer and brought up to processing layer
   - Supported shared scans is also a big plus

2. Versioning

3. Batching and Asynchronous Communication

SQL-over-NoSQL Architecture cont.

- What are the distributed KVS requirements to efficiently implement the SQL-over-NoSQL architecture?

1. Scans

2. Versioning
   - Different versions of each record should be maintained in order to return the right version depending on the timestamp of the transaction
   - This is important of Multi-Version Concurrency Control
   - Garbage collection should be able to reclaim storage occupied by old record versions

3. Batching and Asynchronous Communication

SQL-over-NoSQL Architecture cont.

- What are the distributed KVS requirements to efficiently implement the SQL-over-NoSQL architecture?

1. Scans

2. Versioning

3. Batching and Asynchronous Communication
   - OLTP processing nodes should be able to batch several requests to the storage layer
   - Cost of round-trip messages from processing to storage layer can be **amortized** for multiple concurrent transactions
   - Batch requests should also be executed asynchronously

Difficulties of Building the Optimal KVS

- The conditions for the three requirements conflict one another
- As a result, more KVS today, with the exception of Kudu, are specifically designed for get/put requests
- There are many **locality conflicts** that surface when we try to integrate scans into these systems

Locality Conflicts

SCAN vs..

1. Get/Put
2. Versioning
3. Batching

Locality Conflicts

SCAN vs..

1. Get/Put
   - Systems designed for analytical queries normally use columnar layouts to increase locality
     - This is so queries can access the same set of memory locations repetitively over a short period of time
   - Existing KVS typically favor row-store layouts for processing get/put requests without the need to materialize records
2. Versioning
3. Batching

Locality Conflicts

SCAN vs..

1. Get/Put

2. Versioning
   - The presence of irrelevant versions of records reduces locality and slows down scan operations
   - Checking the relevance of a record version as part of a scan can be very costly
3. Batching

Locality Conflicts

SCAN vs..

1. Get/Put

2. Versioning

3. Batching
   - It is not ideal to batch scan operations with get/put requests
   - OLTP workloads require constant and predictable get/put response times
     - Scan operations are highly variable in terms of latency, depending on the selectivity of the predicates and the number of columns that needs processing during a query

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Design Space

The main decisions when designing a storage engine:

- How to **store** data?
- How to **access** data?
- How to **update** data?

Design Space

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	
Layout	**column (PAX)**	scan	get/put
	row	get/put	scan
Versions	**clustered**	get/put	GC
	chained	GC	scan

Table 2: Design Tradeoffs

Design Space - how to read

Dimension	*Approach*	*Advantages*	*Disadvantages*
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Table 2: Design Tradeoffs

Design Space - how to read

Measurements:

storage - how efficient is the storage in terms of fragmentation

concurrency - how well is it supported

versioning - how costly is it to implement (performance wise)

GC - how costly is it to implement (performance wise)

get/put - efficiency for get/put operations

scan - efficiency for scan operations

Dimension	*Approach*	*Advantages*	*Disadvantages*
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Table 2: Design Tradeoffs

Garbage Collection

A form of memory management

“Garbage” - useless/obsolete data that is occupying valuable memory space

Advantages:

- Ease of development
- Mitigates certain bugs and memory leaks

Disadvantages:

- Impacts performance

Why do we need to consider GC when designing a key-value store (why can’t we just manually manage our memory)?

Design Space - how to read

Measurements:

storage - how efficient is the storage in terms of fragmentation

concurrency - how well is it supported

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Table 2: Design Tradeoffs

Update: update-in-place

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	

1	Foo	23
2	Bar	44

Page

Records are fixed-size

Update: update-in-place

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
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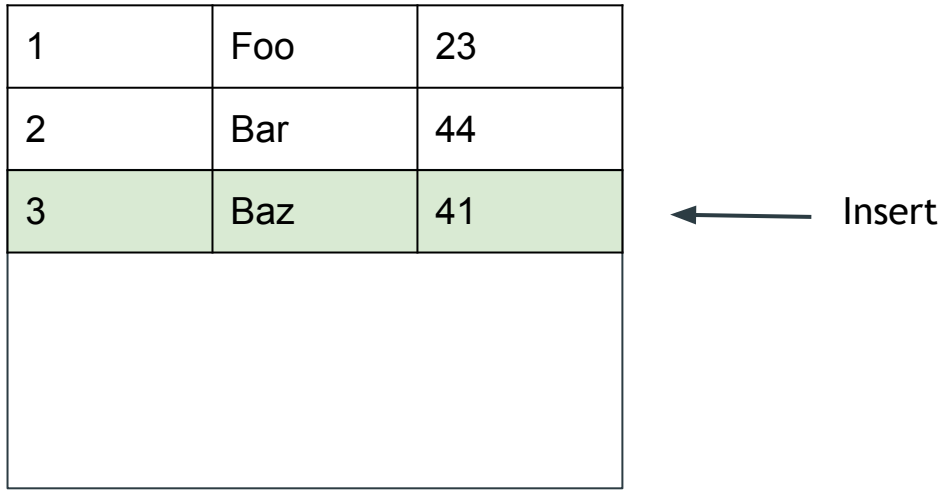

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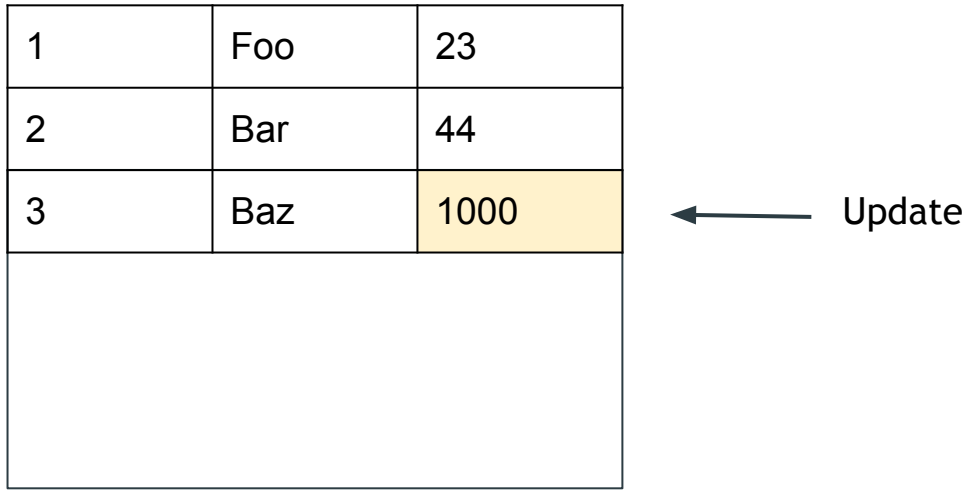

Update: update-in-place

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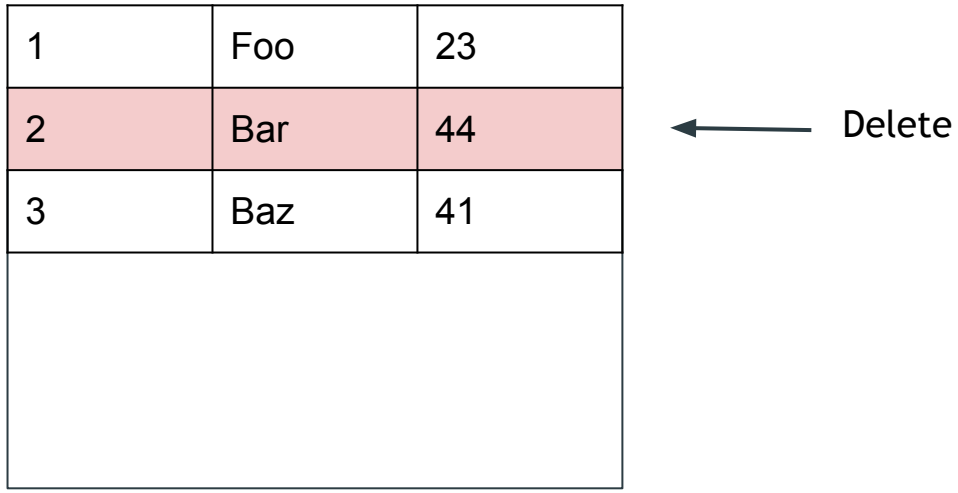

Update: update-in-place

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
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	delta-main	compromise	

1	Foo	23
3	Baz	41

Page

Update: update-in-place

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	

1. Why is storage an advantage of update-in-place (assuming fixed record sizes)?
2. Why are versioning and concurrency disadvantages?

Measurements:

storage - how efficient is the storage in terms of fragmentation

concurrency - how well is it supported

versioning - how costly is it to implement

GC - how costly is it to implement

get/put - efficiency for get/put operations

scan - efficiency for scan operations

Update: log-structured

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	

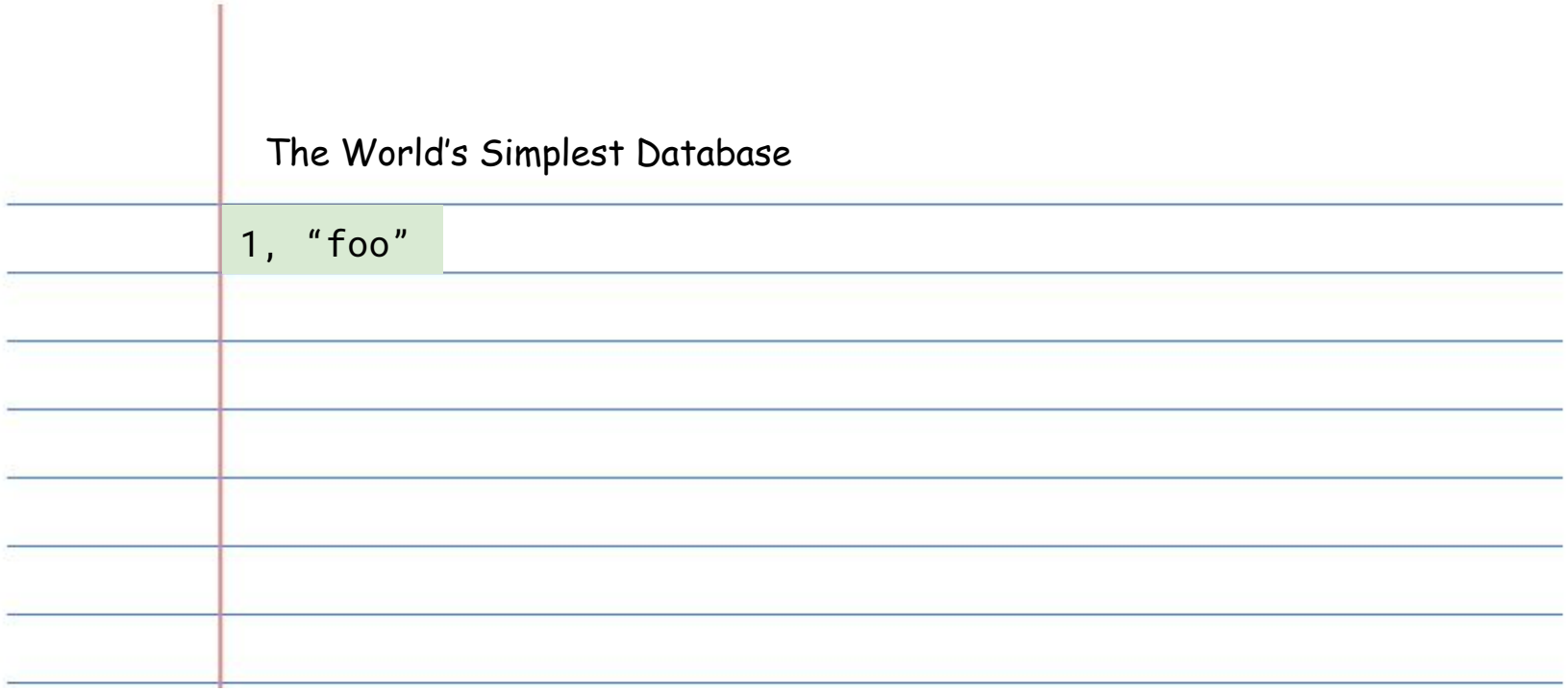
No overwriting necessary, just append to a log.

Introducing

Two methods:
`get(k)`
`put(k,v)`

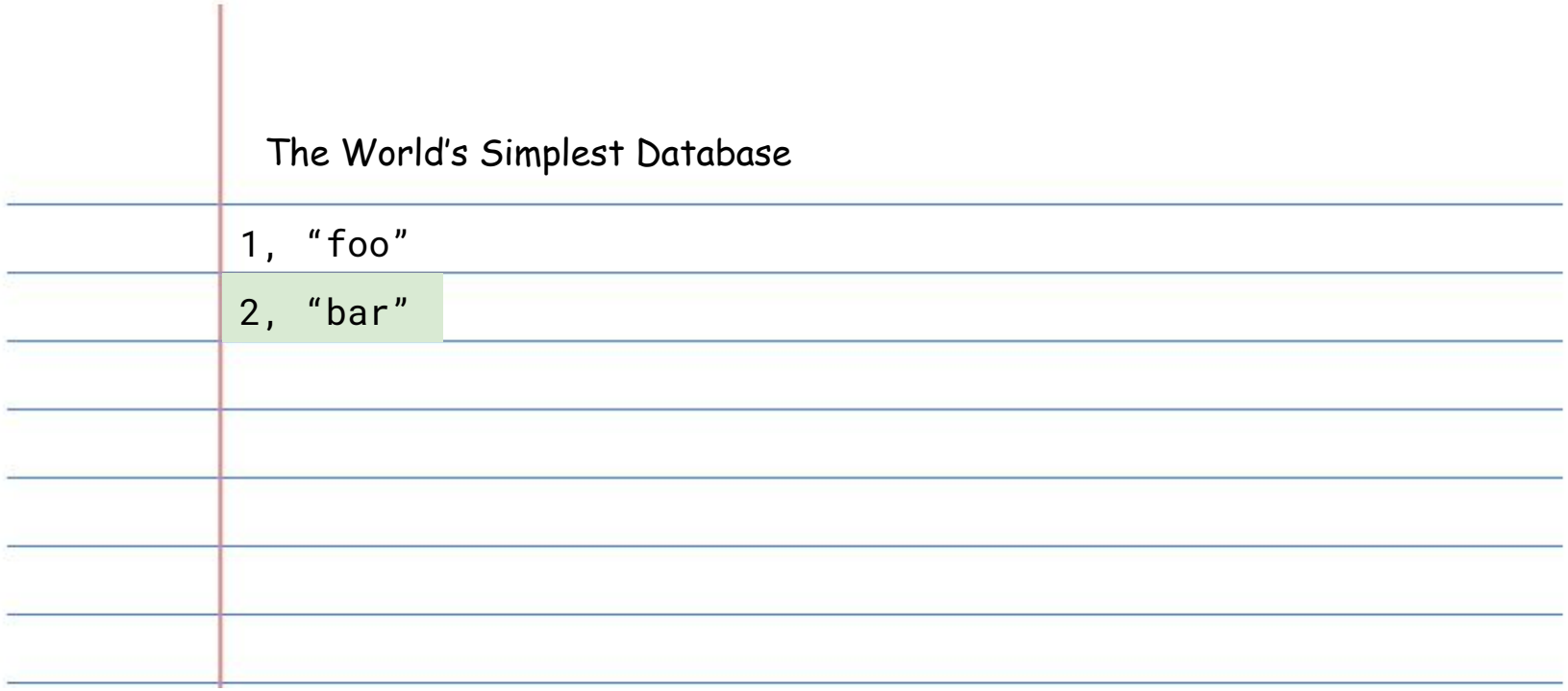
Insert 1

```
put(1, "foo")
```



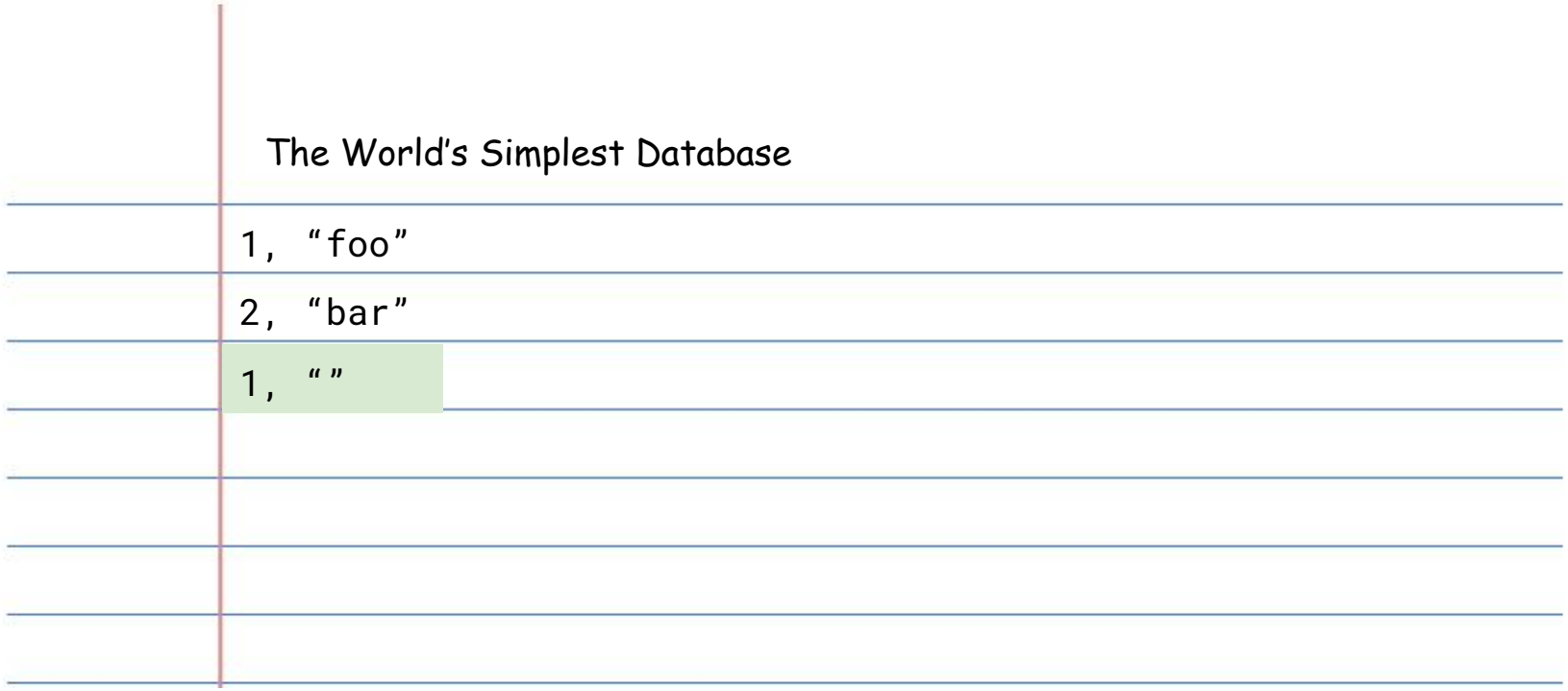
Insert 2

```
put(2, “bar”)
```



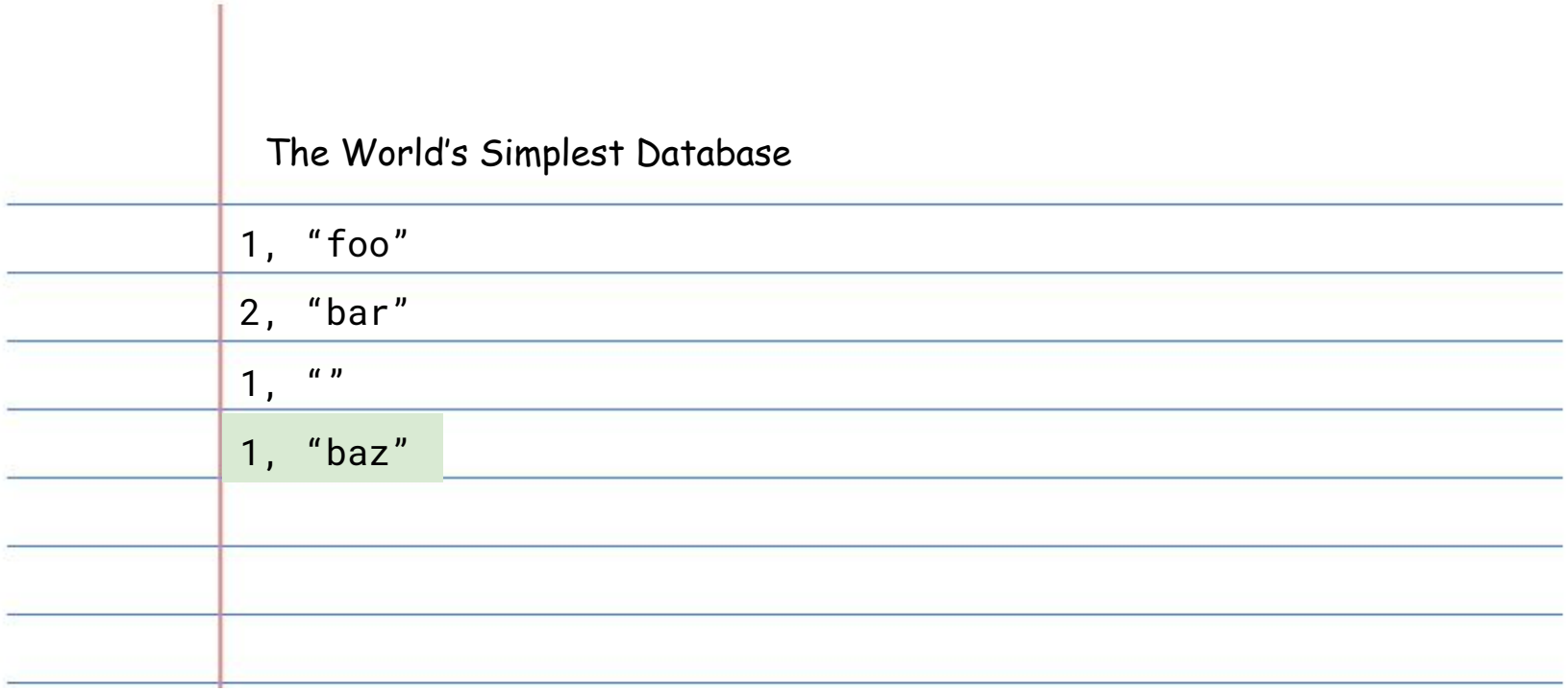
Delete 1

```
put(1, "")
```



Update 1

```
put(1, “baz”)
```



Get 1

```
get(1) =
```

Get 1

```
get(1) =
```

Get 1

```
get(1) =
```

Get 1

```
get(1) = “baz”
```

Update: log-structured

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	

Measurements:

storage - how efficient is the storage in terms of fragmentation

concurrency - how well is it supported

versioning - how costly is it to implement

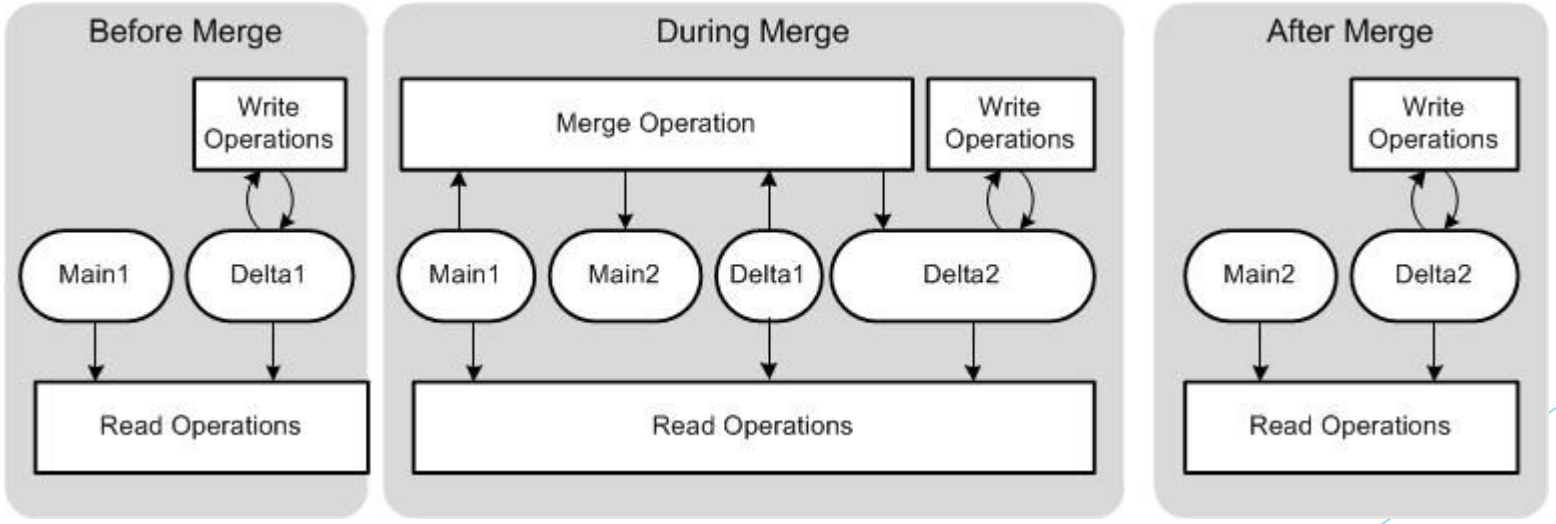
GC - how costly is it to implement

get/put - efficiency for get/put operations

scan - efficiency for scan operations

Update: delta-main

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	



Update: delta-main

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	

This approach tries to combine the advantages of the log-structured approach (fast get/put) with the advantages of update-in-place (fast scans).

Layout

Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	
Layout	**column (PAX)**	scan	get/put
	row	get/put	scan
Versions	**clustered**	get/put	GC
	chained	GC	scan

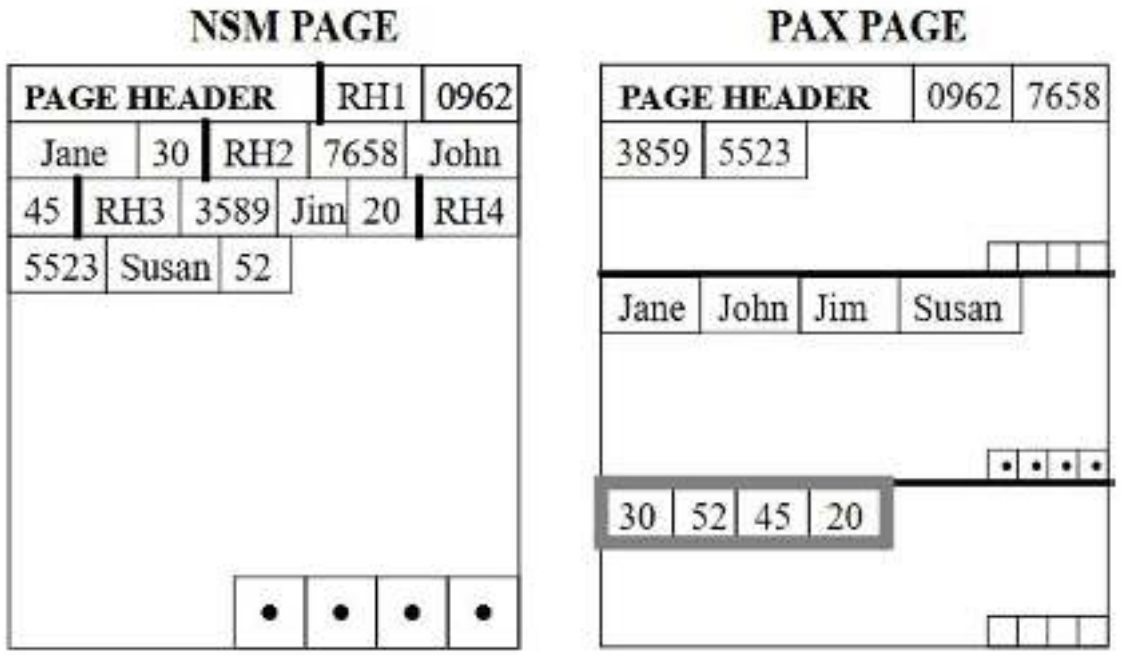
Table 2: Design Tradeoffs

PAX - Partition Attributes Across Paradigm

- Variant of column-major ordering
- PAX is a compromise between the pure column and row-major designs.

PAX - Partition Attributes Across Paradigm

- Stores a set of records in every page, but within the page, all records are stored in a column-major representation.



https://www.pdl.cmu.edu/PDL-FTP/Database/pax.pdf

Versions

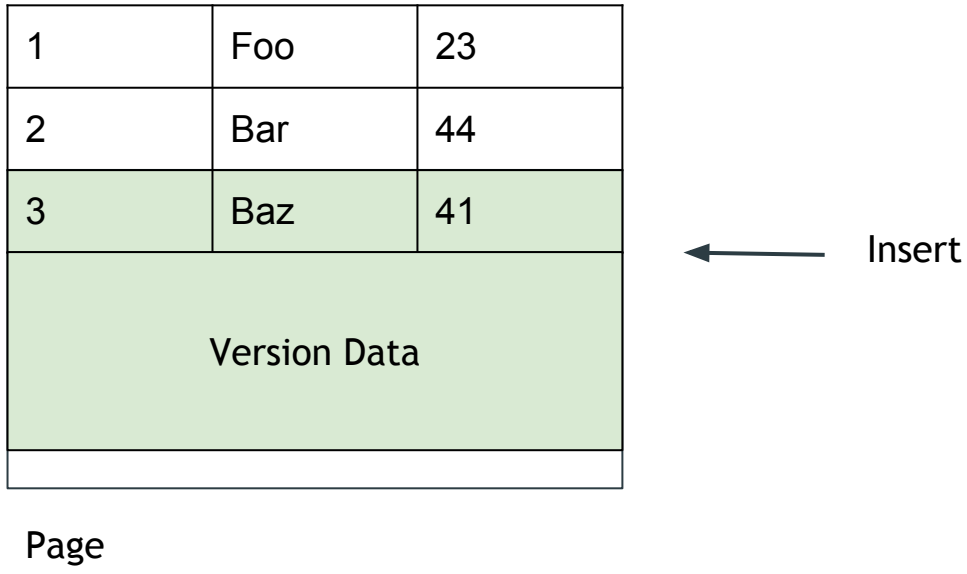
Dimension	*Approach*	*Advantages*	*Disadvantages*
Update	**update-in-place**	storage	versioning, concurrency
	log-structured	storage, concurrency	GC
	delta-main	compromise	
Layout	**column (PAX)**	scan	get/put
	row	get/put	scan
Versions	**clustered**	get/put	GC
	chained	GC	scan

Table 2: Design Tradeoffs

Versions - clustered

Versions	**clustered**	get/put	GC
	chained	GC	scan

- Stores all versions of a record in the same location



Versions - chained

Versions	**clustered**	get/put	GC
	chained	GC	scan

- Chain the versions in a linked list

Garbage Collection - 2 strategies

Periodic garbage collection in a separate dedicated thread/process

Piggy-back garbage collection with (shared) scans

Design Space

(update-in-place vs. log-structured vs. delta-main)
×(row-major vs. column-major / PAX)
×(clustered-versions vs. chained-versions)
×(periodic vs. piggy-backed garbage collection)

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TellStore-Log

Update: Log-structured

Layout: Row-major

Versions: Chained Versions

Garbage collection: Piggy-backed

TellStore-Log

Update: Log-structured

Layout: Row-major

Versions: Chained Versions

Garbage collection: Piggy-backed

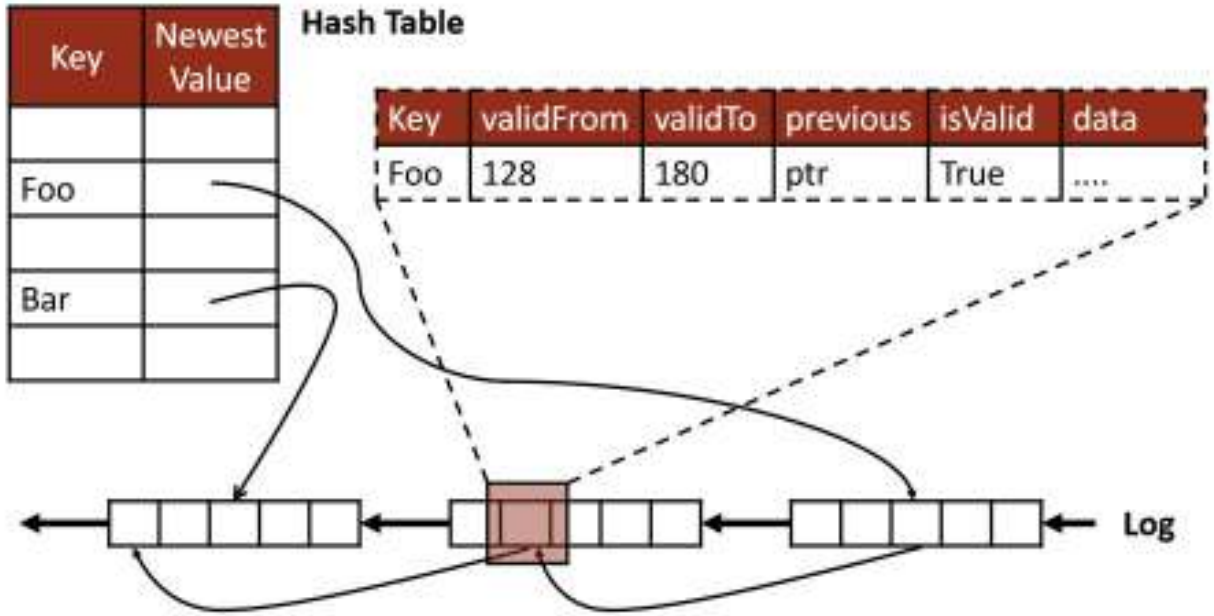

Figure 2: Data Structures of TellStore-Log

TellStore-Log

Questions for discussion:

- Why did the paper use a hash index to implement this log-structured storage (as opposed to eg. a tree index)?
- Why does TellStore-Log have good scan performance compared to other log-structured designs (such as RAMCloud)?

TellStore-Col

Update: Delta-main

Layout: Column-major

Versions: Clustered Versions

Garbage collection: Periodic

TellStore-Col

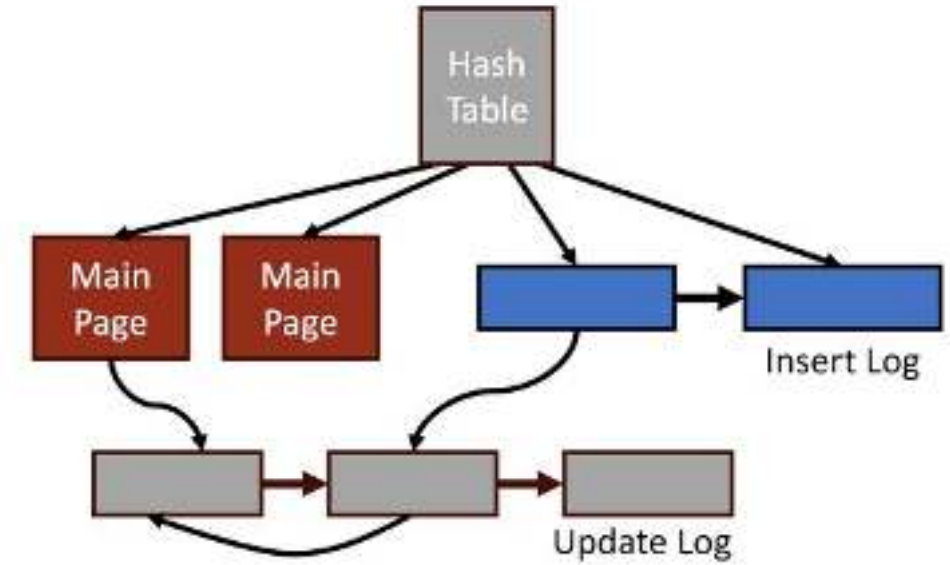

Figure 3: Delta-Main Approach

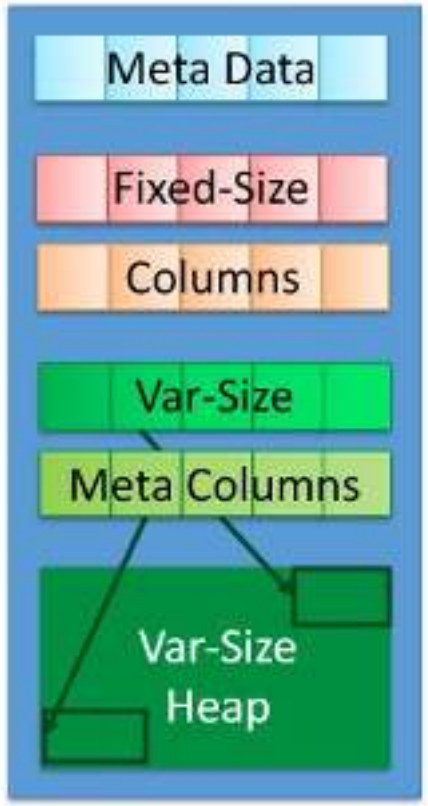

Figure 4: ColumnMap

TellStore-Col

Questions for discussion:

- Why is the “delta” split into two logs - insert log and update log?
  - (Hint: A different log is used depending on whether the key exists or not)
- What are the advantages of TellStore-Col vs TellStore-Log?

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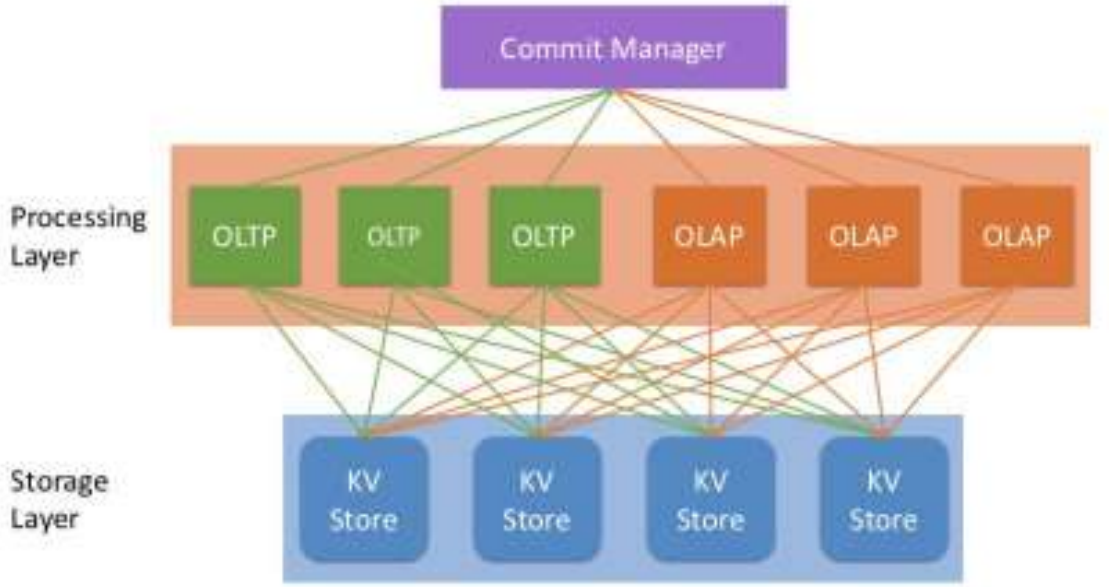
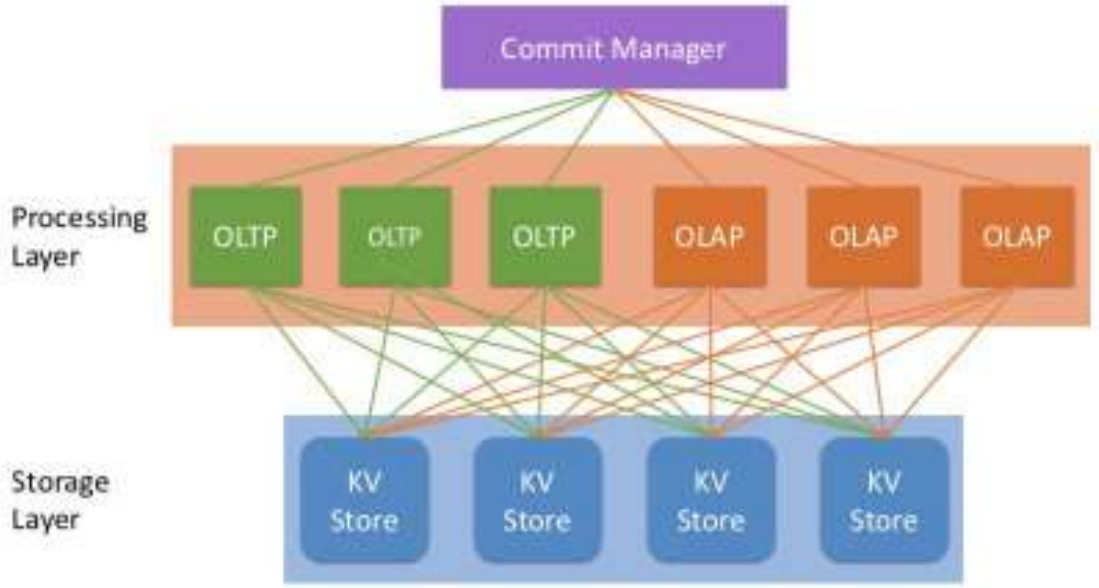
Implementation

- This section describes TellStore as a distributed, in-memory KVS, that can use any of the storage engines described above
  - Communication model
  - Thread model
  - Data indexing
  - Predicate pushdowns



Implementation - Communication Model

- Batching + Async Communication
- A processing instance should not be idle while waiting for a storage request to complete
  - otherwise wasted CPU and network bandwidth



Batching requests from the processing layer and responses from storage cuts down on the messaging rate, which would otherwise be a bottleneck.

Implementation - Thread Model

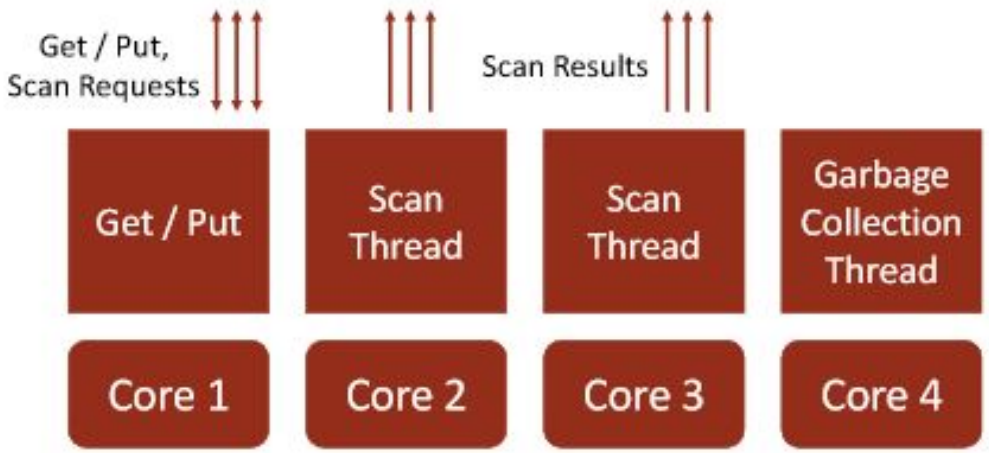
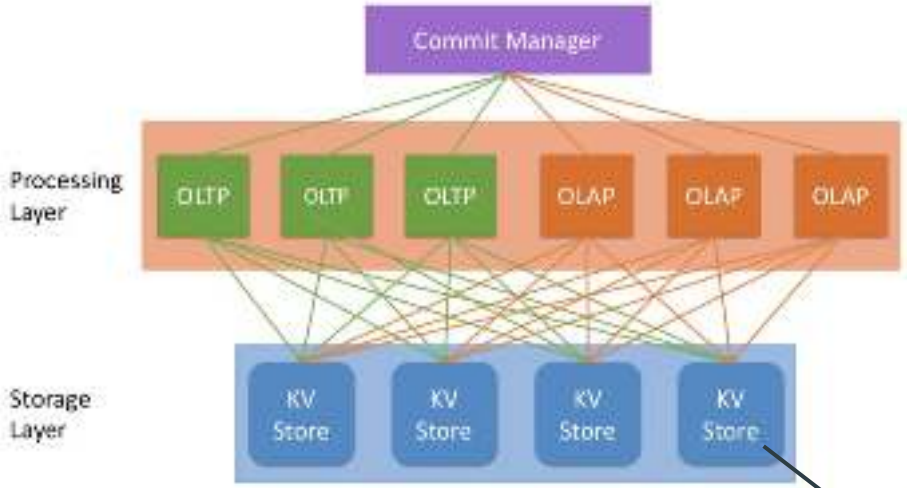


Figure 5: TellStore Thread Model

Why this thread model? In other words, what is the benefit of having separate threads for scans and gets/puts?

Implementation - Data Indexing



What about indexing across KV stores? How do we know which KV Store contains the key we want? Simple if we only have a few instances, but what if we have many KV Stores?

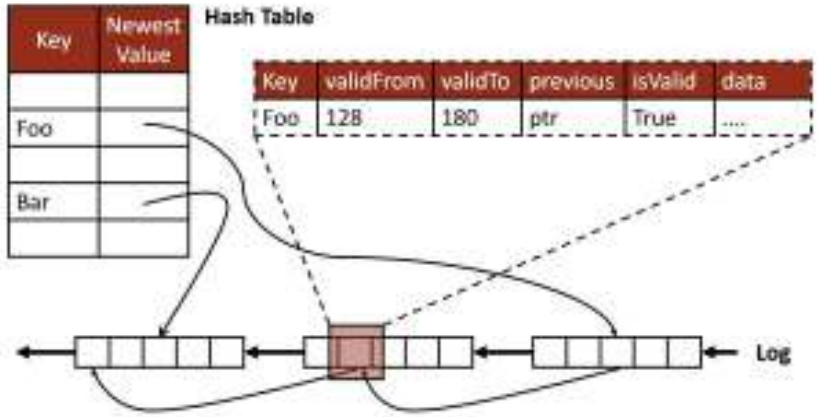
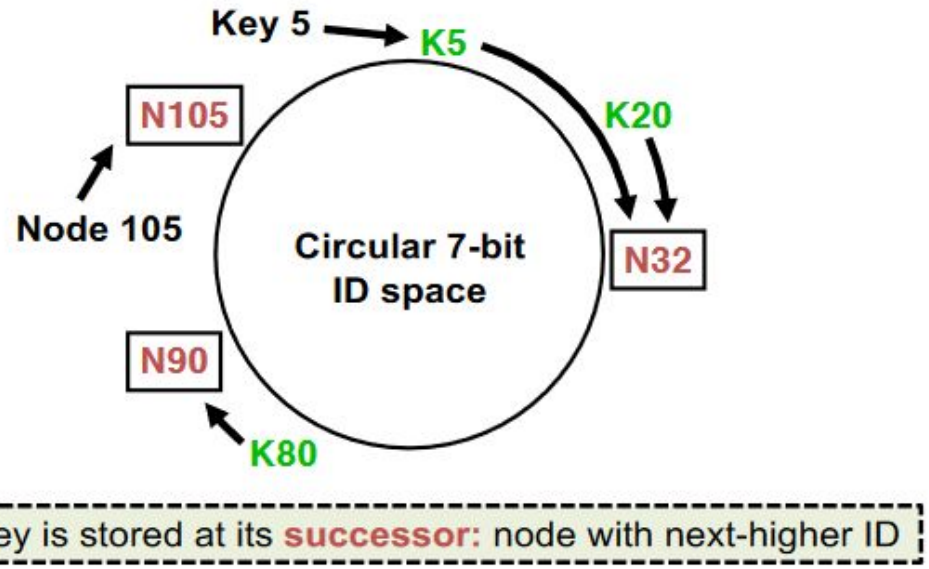


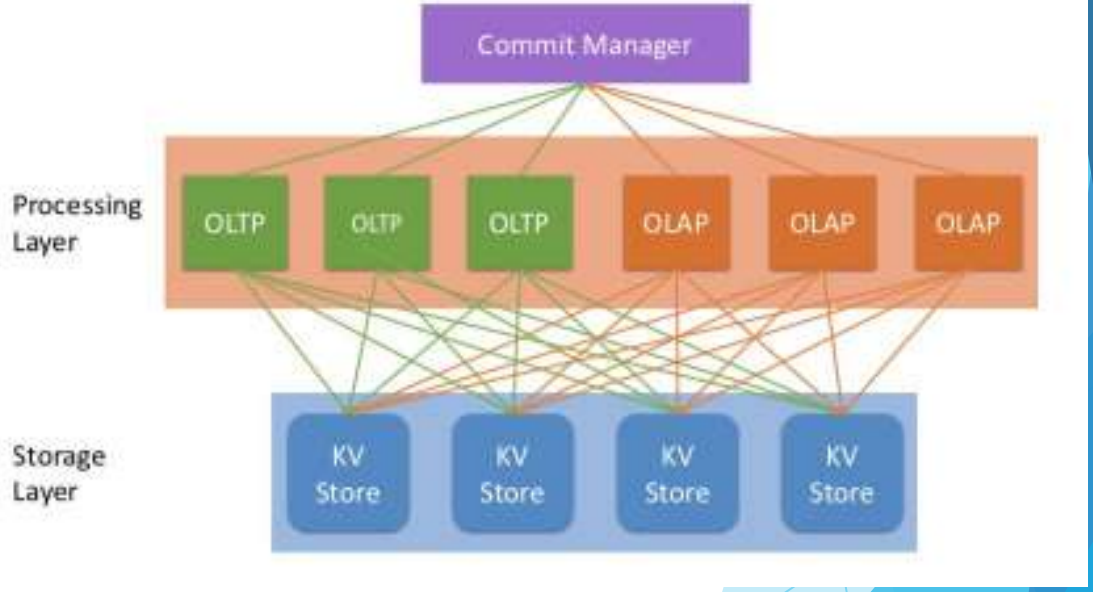
Figure 2: Data Structures of TellStore-Log

Implementation - DHT

Consistent hashing [Karger '97]



Key is stored at its **successor:** node with next-higher ID



Source: https://www.cs.princeton.edu/courses/archive/fall16/cos418/docs/L10-dhts.pdf

Implementation - Predicate Pushdowns

Pushing down predicates allows for less data movement. Imagine:

```
SELECT * FROM A,B WHERE A.id=B.id AND A.name="John";
```

Implementation - Predicate Pushdowns

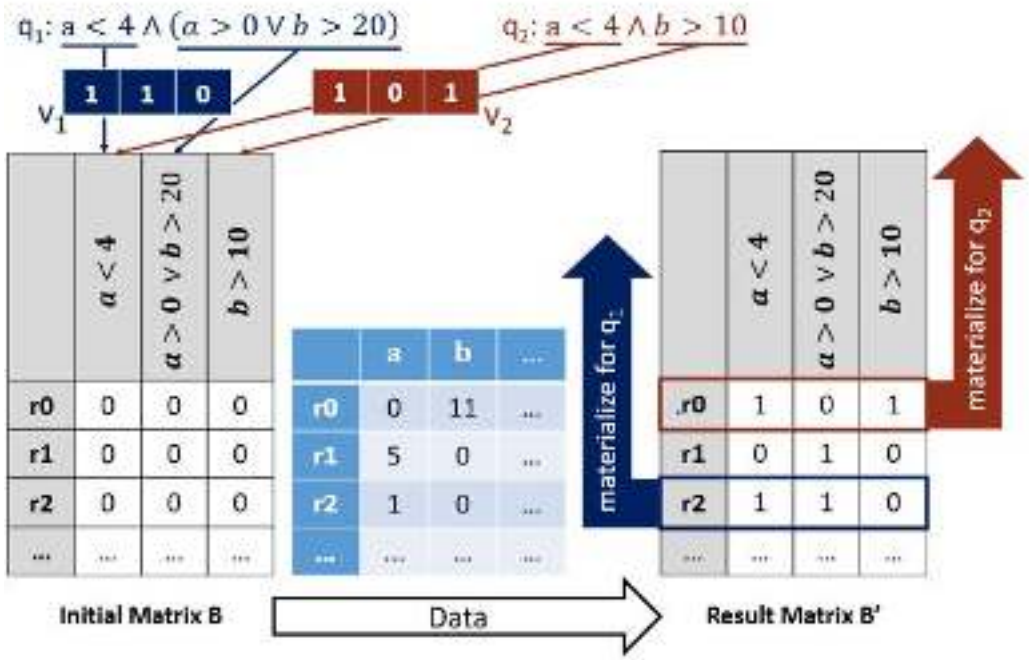


Figure 6: Predicate Evaluation and Result Materialization

- TellStore requires all selection predicates of scans to be in conjunctive normal form (CNF).
- CNF - a conjunction of one or more clauses, where a clause is a disjunction of literals; otherwise put, it is an AND of ORs.

$$(A \vee B) \wedge C$$

$$(A \wedge B) \vee C$$

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Experimental Setup

- Test environment
  - All experiments were done on a cluster of 12 machines
  - All KVS benchmarked are Non-uniform Memory Access (NUMA) unaware
  - 3x the number of processing nodes as storage nodes were used to prevent load generation from becoming the bottleneck

- TellStore-Col was the main test subject against all other KVS
- Kudu performances were used as a baseline for all the experiments

- Running the experiment
  - First populate the data, then run the experiment for 7 minutes total
  - First and last minute were factored out due to warm-up and cool-down effects

Experimental Benchmarks

1. Yahoo! Cloud Serving Benchmark (YCSB)
   - Commonly referred to as “Big Data” Benchmark
   - The YCSB benchmark was the designated goal performance for cloud data serving systems, in particular for transaction-processing workloads

2. Extended YCSB → YCSB#
   - Specially crafted to test additional capabilities of a KVS
   - Schema was extended to include variable-size columns and 3 new queries that involve scans
   - Scaling factor dictating the number of tuples in the database was set to 50
     - Corresponds to a test set of 50 million tuples

Side note about NUMA-unaware

When you have multiple physical cores, each core might have their own cache rather than a shared pool of memory and it’s faster to access each core’s local cache rather than the shared memory bus.
An NUMA-Unaware system simply means that the system does not take this access times into account.

YCSB# Queries

Query 1: A simple aggregation on the first floating point column to calculate the maximum value:

```
SELECT max(B) FROM main_table
```

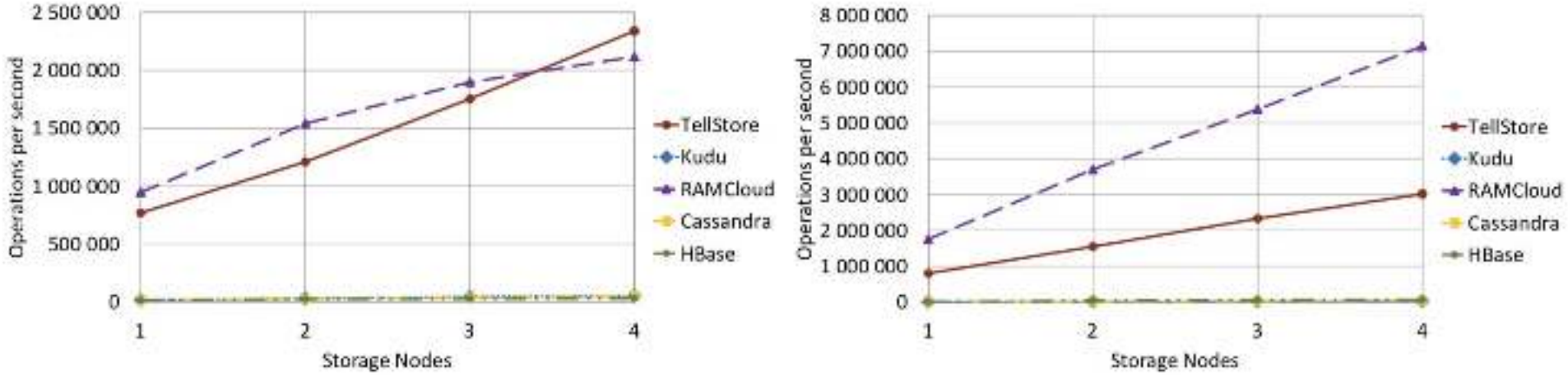
Query 2: The same aggregation as Query 1, but with an additional selection on a second floating point column and selectivity of about 50%:

```
SELECT max(B) FROM main_table
WHERE H > 0 and H < 0.5
```

Query 3: A selection with approximately 10% selectivity:

```
SELECT * FROM main_table
WHERE F > 0 and F < 26
```

Experiment 1: Get/Put Workload



(a) Get/Put Workload

(b) Get-only workload

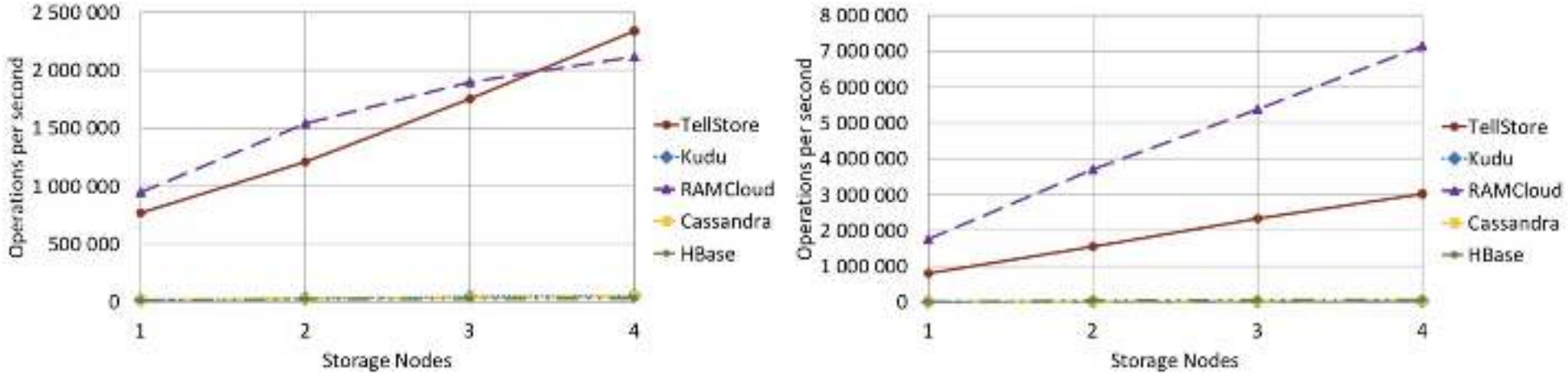
Figure 7: Exp 1, Throughput: YCSB, Various KVS, Vary Storage Nodes

- Tested with traditional YCSB benchmark, no bulk queries
- Get/Put contains 50% update requests consisting of ⅓ inserts, ⅓ updates and ⅓ deletes
- Database size is kept constant with equal amounts of inserts and deletes

Results:

- TellStore performs much better than all others EXCEPT RAMCloud
  - RAMCloud is a distributed in-memory KVS that's highly tuned and specifically designed for these kinds of queries (get/put)
  - RAMCloud is normally seen as the upper bound of the best performance

Experiment 1: Get/Put Workload



(a) Get/Put Workload

(b) Get-only workload

Figure 7: Exp 1, Throughput: YCSB, Various KVS, Vary Storage Nodes

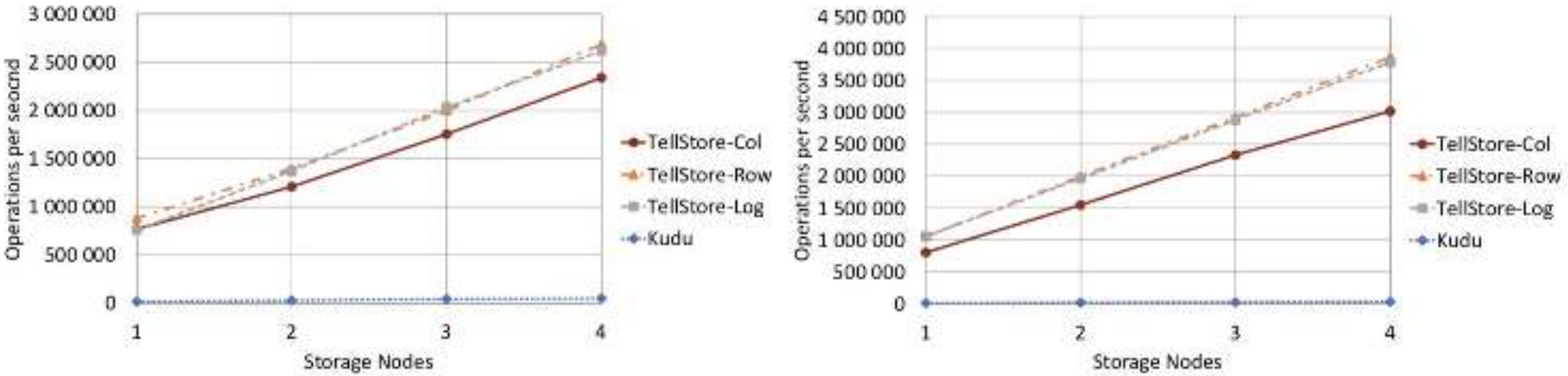
Results:

- Note that all KVS scale linearly with the number of machines
- What does the slope have to do with the system's scalability?

  The steeper the slope, the more "scalable" it is with the number of machines; the more machines you add, the more operations processed

- RAMCloud's scalability issue as shown in (a) might have been due to sub-optimal garbage collection implementation

Experiment 1: Get/Put Workload



(a) Get/Put Workload

(b) Get-only workload

Figure 8: Exp 1, Throughput: YCSB, TellStore Variants and Kudu, Vary Storage Nodes

- TellStore-Log and TellStore-Row outperformed TellStore-Col
- Analysis of TellStore-Col with get/put workload
  - Write-optimized (row-oriented) log in the data helped process Update operations
  - It is more costly to materialize records from columns during Get operations

Experiment 2: Batching

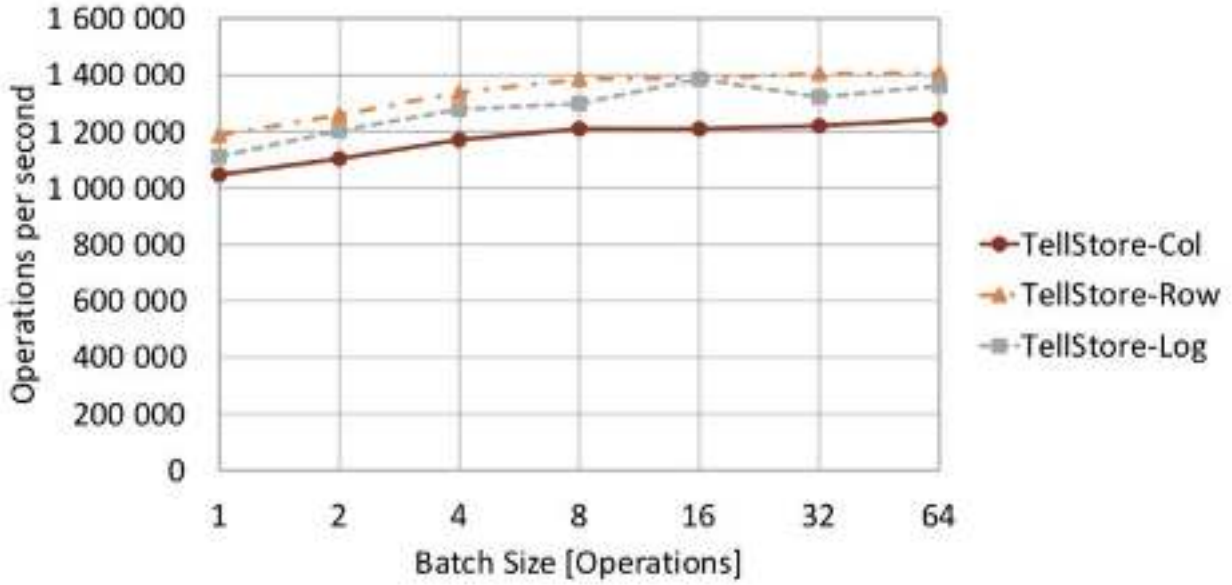


Figure 9: Exp 2, Throughput: YCSB, Vary Batch, 2 Storage Nodes

- As covered in previous sections, processing layer uses batching to improve get/put throughput, but at the cost of increased latency
- The bigger the batch size, the better the throughput for all variants
- Effects however, are not significant enough to say that getting the correct batch size settings is fundamentally important

Experiment 3: Scans

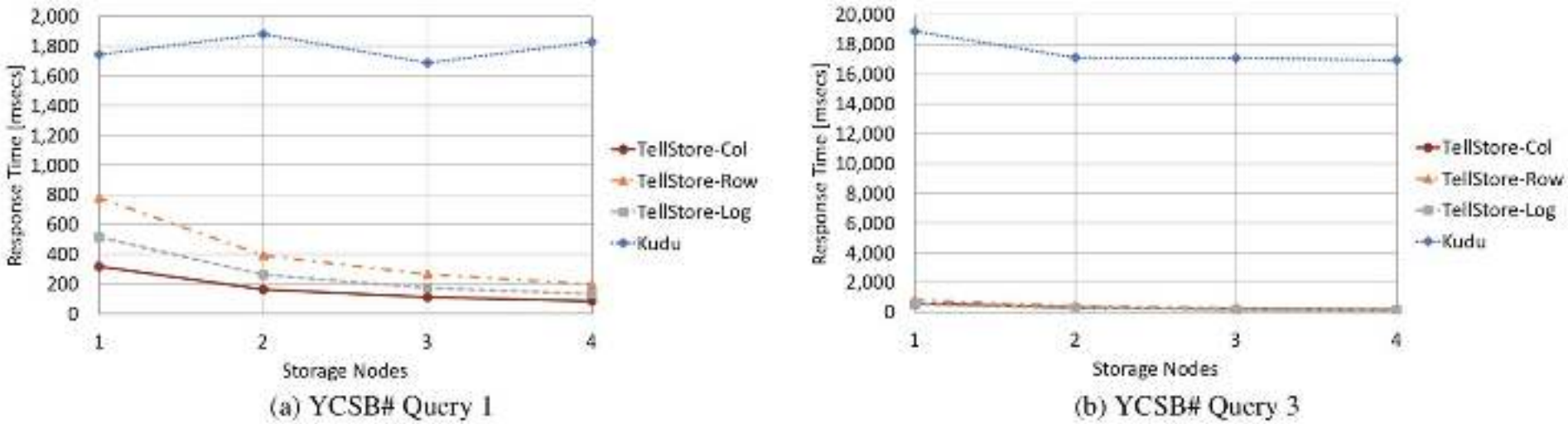
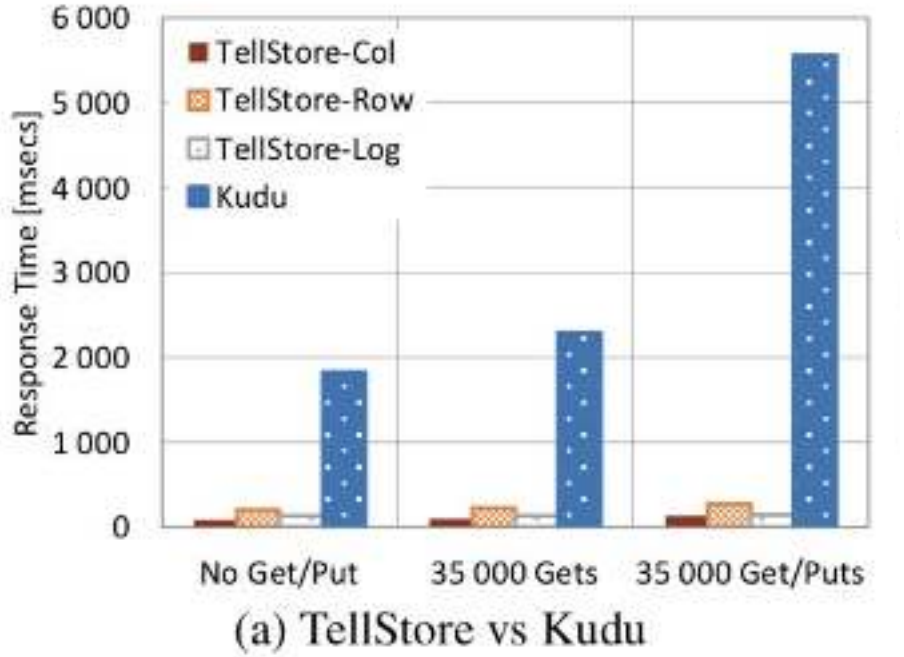


Figure 10: Exp 3, Response Time: YCSB#, Vary Storage Nodes

- YCSB# scan queries were ran in isolation without concurrent get/put workload

- TellStore-Log was slightly faster than TellStore-Col in Query 3
  - This was because Query 3 **has no projections**
  - Read-only workload of Query 3 is the best case for scans in TellStore-Log
    - Scan does not need to perform garbage collection
    - Scan is not affected by data fragmentation

Experiment 4: Hybrid Workloads



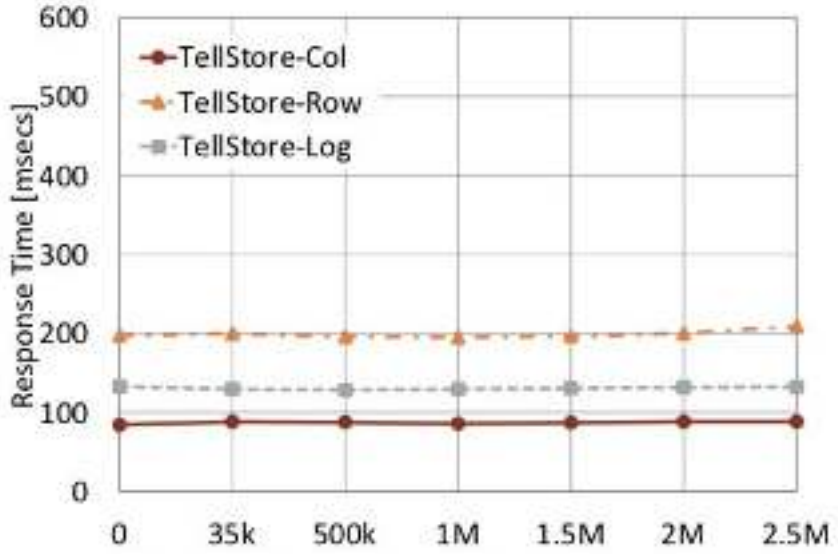
(a) TellStore vs Kudu

- Displays average response time of Query 1 from YCSB#
- Tested on a fixed get/put workload of 35,000 operations per second, because that's Kudu's maximum workload sustainability

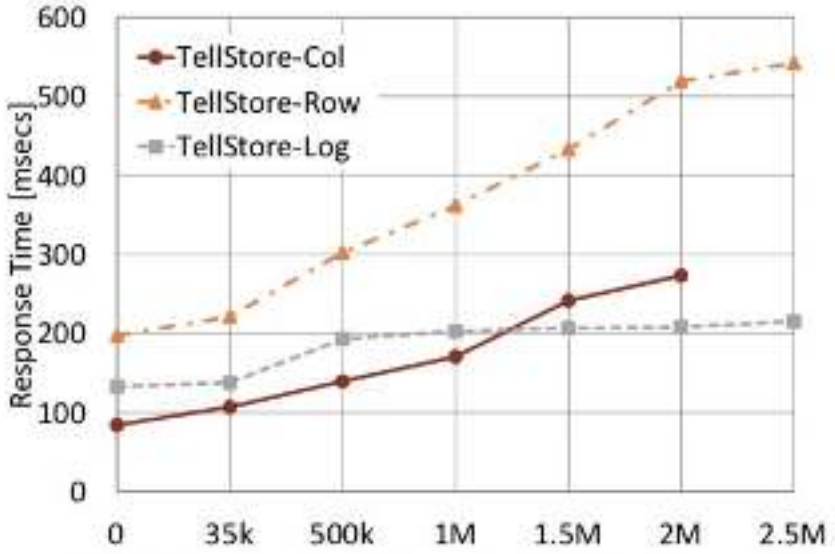
Results:

- Even though Kudu has a columnar design favorable towards Query 1, its overall performance was worse than the TellStore variants
- TellStore-Log does fairly well because in this workload, update requests are kept at a moderate thus fairly high locality was maintained to support scan performance

Experiment 4: Hybrid Workloads



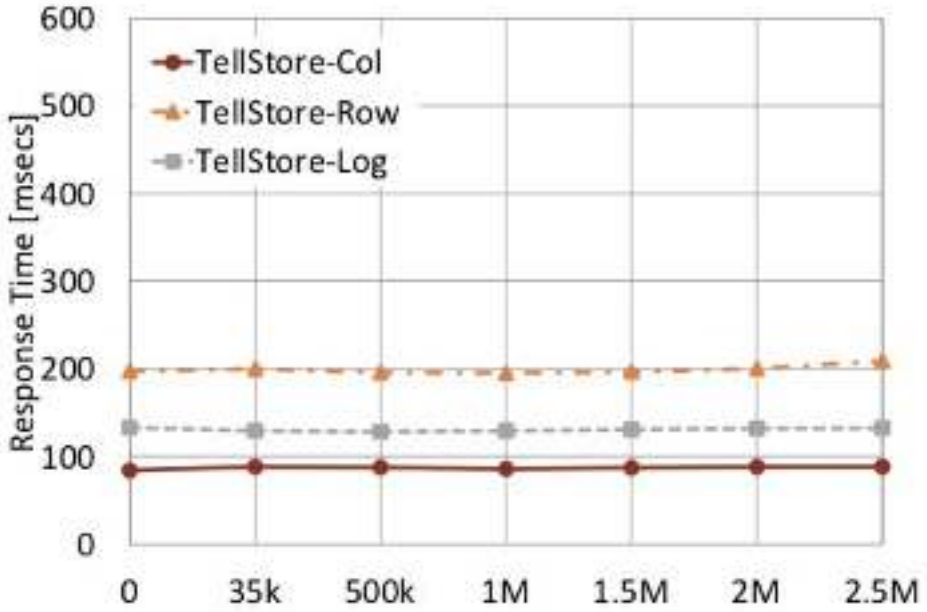
(b) TellStore, Scale Get Requests



(c) TellStore, Scale Get/Put Requests

- Displays response time of Query 1 for the separate TellStore variants when we scale **beyond 35,000 operations per second**

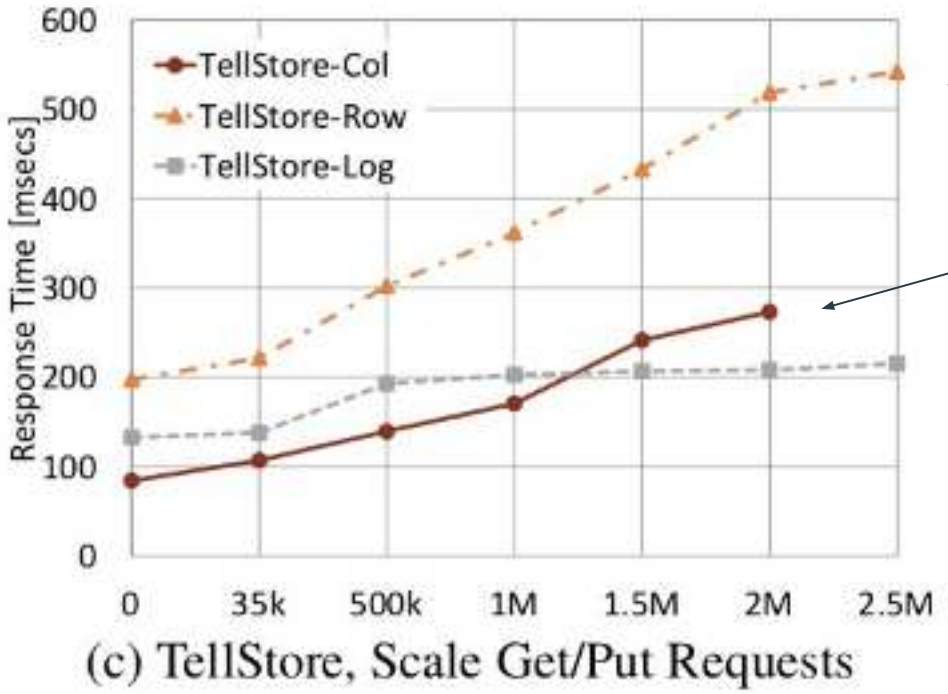
Experiment 4: Hybrid Workloads



(b) TellStore, Scale Get Requests

- Response time for Query 1 is constant and independent of the concurrent get workload, why?
  - Scans and get requests are scheduled on different cores in the storage node
  - Scan performance is not impacted by garbage collection, data stored in delta or stale versions of records

Experiment 4: Hybrid Workloads



(c) TellStore, Scale Get/Put Requests

TellStore-Row and TellStore-Col are heavily impacted by concurrent updates

- Increasing update load results in more costly pointer-chasing to the delta for the look up of the latest version of the record

TellStore-Col also does not have any advantage over TellStore-Row with high update workloads, since almost all records are fetched from the row-store delta

- Scan response time is visibly affected by raising the get/put workload
- TellStore-Log would be the best approach
  - After the sharp increase of the average scan response time at 500,000 concurrent get/put requests per second, garbage collection rewrites the entire log with every scan as every page is affected by an update

Experiment 4: Hybrid Workloads

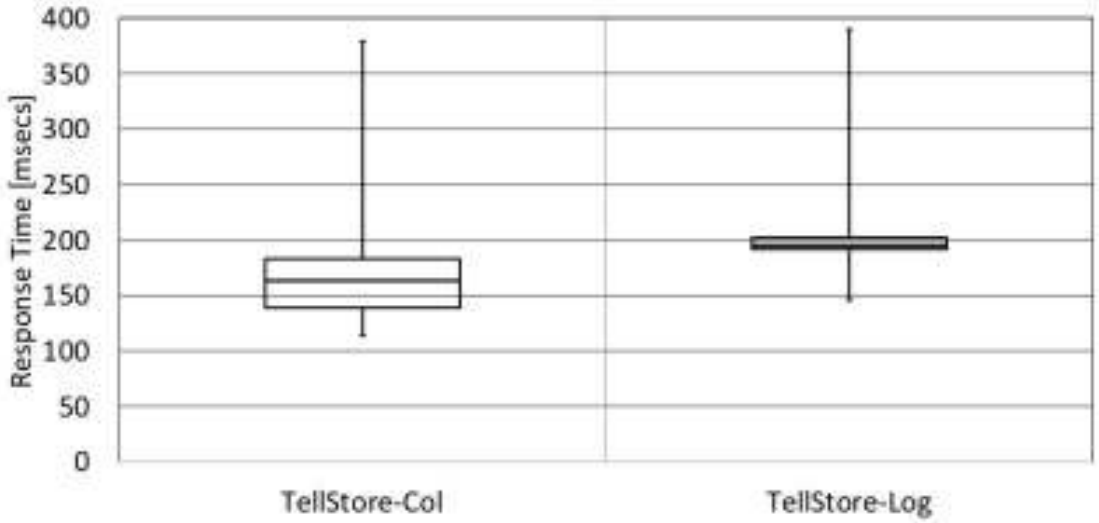


Figure 12: Exp 4, Response Time: YCSB# Query 1
4 Storage Nodes with 1 Mio. concurrent get/put requests

- 1%, 25%, 50%, 75%, and 99% percentile response times of Query 1 with concurrent get/put workload
- Even though TellStore-Col outperforms TellStore-Log at 1 Mio. get/put requests, TellStore-Log is still better overall
  - Scan performance of TellStore-Log is dependent on delta size
    - Before GC, delta size is large so scan is slow
    - After GC, delta size is small so scan is fast
  - Roughly constant response time in TellStore-Log with piggy-backed garbage collection

Experiment 5: Huawei-AIM Benchmark

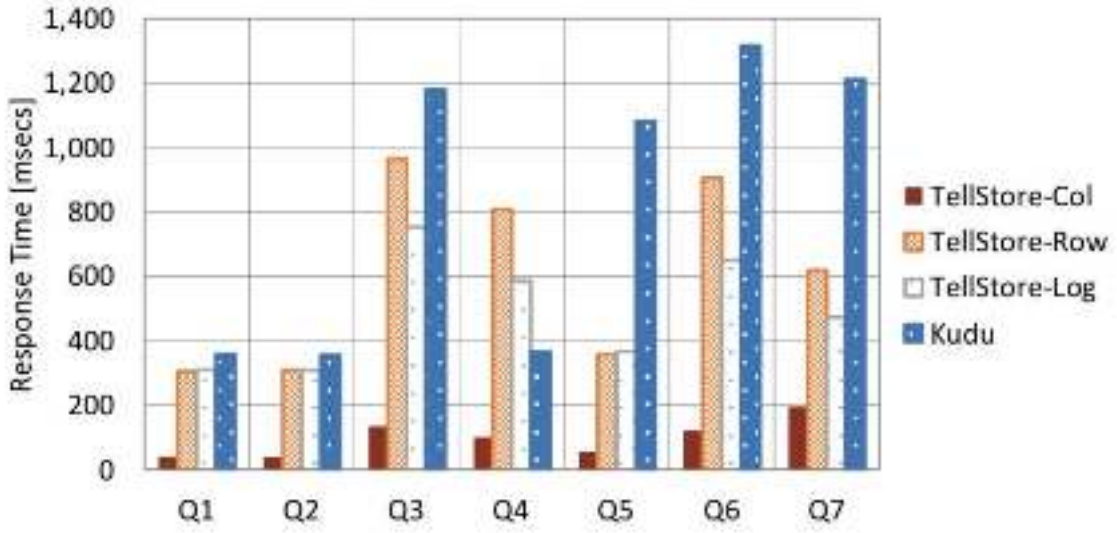


Figure 13: Exp 5, Resp. Time: Huawei-AIM Workload

- This experiments strives to show that TellStore also performs well against more complex, interactive workloads
- Workload is defines 7 analytical queries with concurrent get/put workload of 40,000 operations per second
- There was not much different when scan was ran in isolation, hence these are the results for concurrent workloads

Experiment 5: Huawei-AIM Benchmark

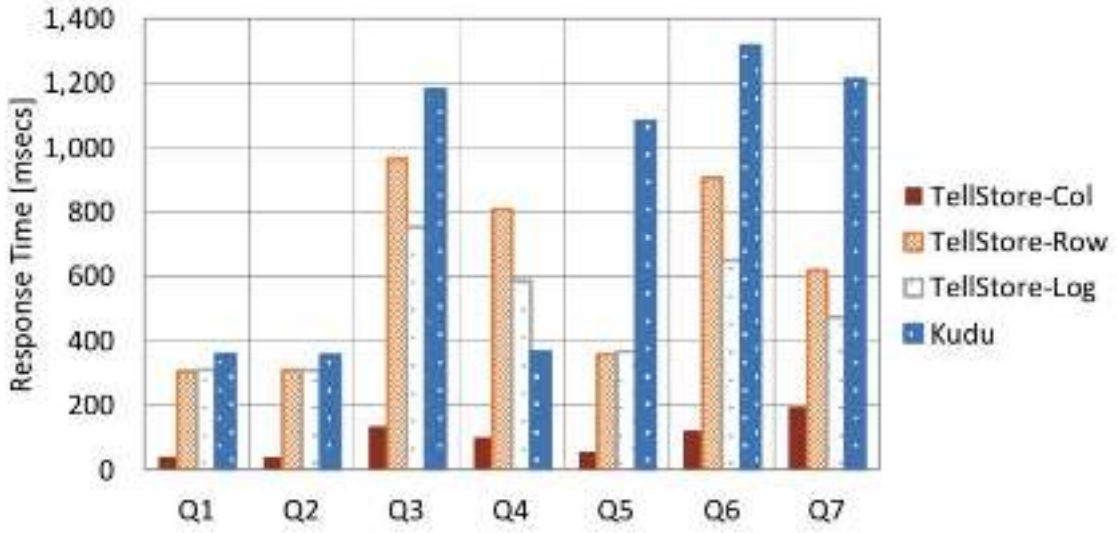


Figure 13: Exp 5, Resp. Time: Huawei-AIM Workload

- TellStore-Col outperformed all others significantly
- Notice that the difference between TellStore-Col and TellStore-Log is the biggest in this experiment, why?
  - This workload was run on a table with more than 500 columns, giving TellStore-Col's columnar layout a bigger advantage

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Related Work

Let's take a look at several other existing KVS:

- Systems that adopted the SQL-over-NoSQL architecture
  - FoundationDB, Hyder, Tell, and AIM
  - FoundationDB, Hyder and Tell were not built to take on analytics; AIM supports read-only analytics and high update rates
- Large-scale Analytical Systems
  - Hadoop, Spark, and DB2/BLUE
  - These systems has significant trouble with or no support for querying live data that is subject to frequent and fine-grained updates
- Systems with good support for hybrid workloads on live data
  - HyPer, HANA, and Hekaton/Apollo
  - TellStore differs from these with its ability to scale out in a distributed system, while the above can only scale up on a single machine
- Document Stores
  - DocumentDB and MongoDB
  - These offer certain scans with secondary indexes which are specifically tuned to document-related use-cases
- TellStore can hopefully be used as a model to further improve these existing KVS systems to achieve a better overall performance

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Conclusion

- It is indeed possible to build a KVS that efficiently supports both **scans for analytics** and **high get/put throughput for OLTP workloads** with TellStore

- The integrated design of TellStore addressed important design questions of a KVS, allowing it to outperform existing ones
- Advanced implementation techniques of TellStore (e.g., piggy-backing garbage collection) helps to mitigate the effects of concurrent update on scan times

- Among the three TellStore variants, we can conclude that TellStore-Col has the best overall performance, followed by TellStore-Log, then TellStore-Row

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Future Research and Advancements

- TellStore currently does not feature **high availability with replication**
  - Replication feature in TellStore is currently being implemented
  - With confirmed observation, replication is orthogonal to all other aspects of a KVS and will not change the main results discovered in this paper
- Getting analytical workloads to run efficiently
  - Having fast scans on KVS only partially solves the issue
  - Explore other analytical queries that can only be efficiently executed in a distributed manner
    - Studies against other distributed query processing systems (e.g., Spark and Presto) using TPC-H benchmark queries
    - TellStore does not have an advantage, since neither Spark nor Presto can efficiently utilize TellStore's scan feature of **shared scans** and **pushing down selections, projections and aggregation to the storage layer**
- Studies against less aggressive variants to carry out garbage collection in TellStore-Col and TellStore-Row
  - Current implementation of garbage collection may result in high contention of memory buss and in-write amplification if data does not fit into main memory