R-Store: A Scalable Distributed System for Supporting Real-time Analytics

Feng Li, M. Tamer Ozsu, Gang Chen,
Beng Chin Ooi

National University of Singapore

ICDE 2014

Background

- Situation for large scale data processing
  - Systems classified into 2 categories: OLTP, OLAP
  - Data periodically transport to OLAP through ETL
- Demand
  - Time critical decision making (RTOLAP)
    - the freshness of OLAP results
    - Fully RTOLAP entail executing query directly on OLTP data
  - OLAP & OLTP processed by one integrated system

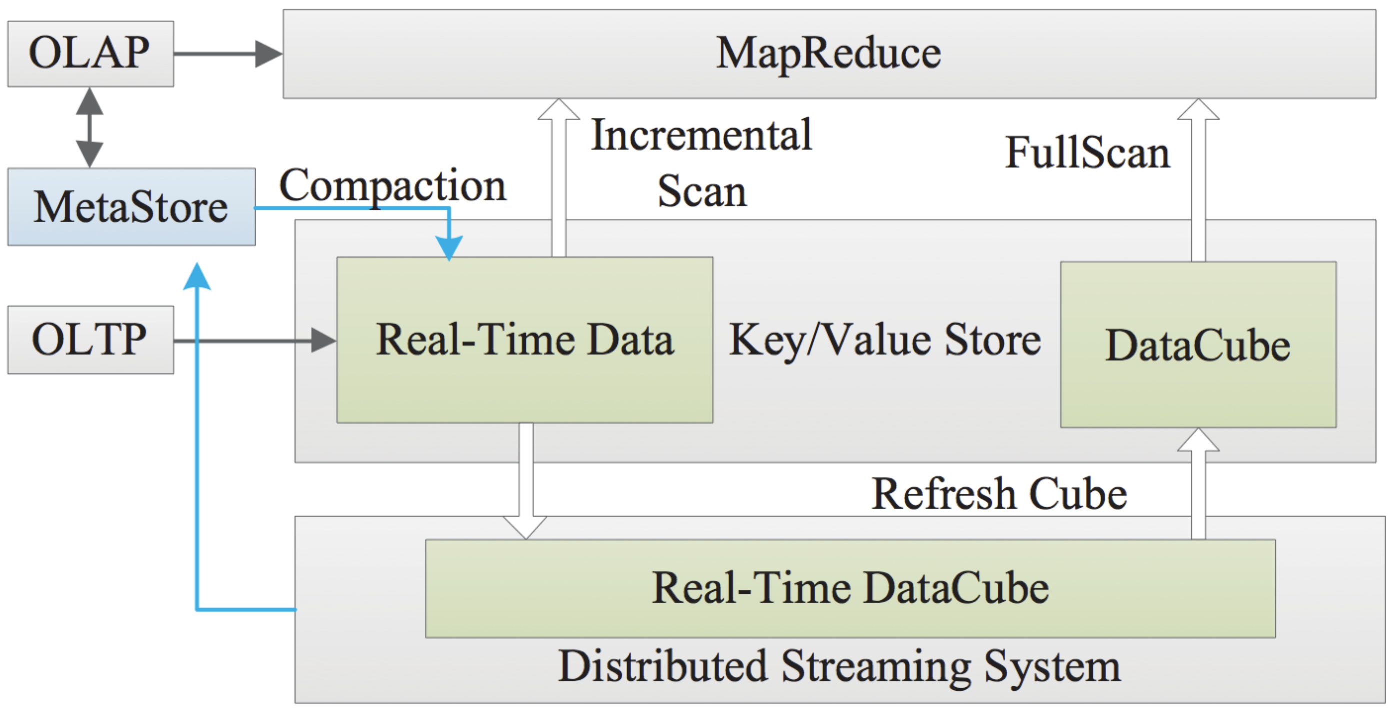
Background

- Problem on simple combination
  - Resource contention
    - OLTP query blocked by OLAP
  - Inconsistency
    - Long running OLAP may access same data sets several times, updates by OLTP could lead to incorrect OLAP results
- Solution – R-Store
  - Resource contention
    - Computation resource isolation
  - Inconsistency
    - Multi-versioning storage system

A glimpse of R-Store

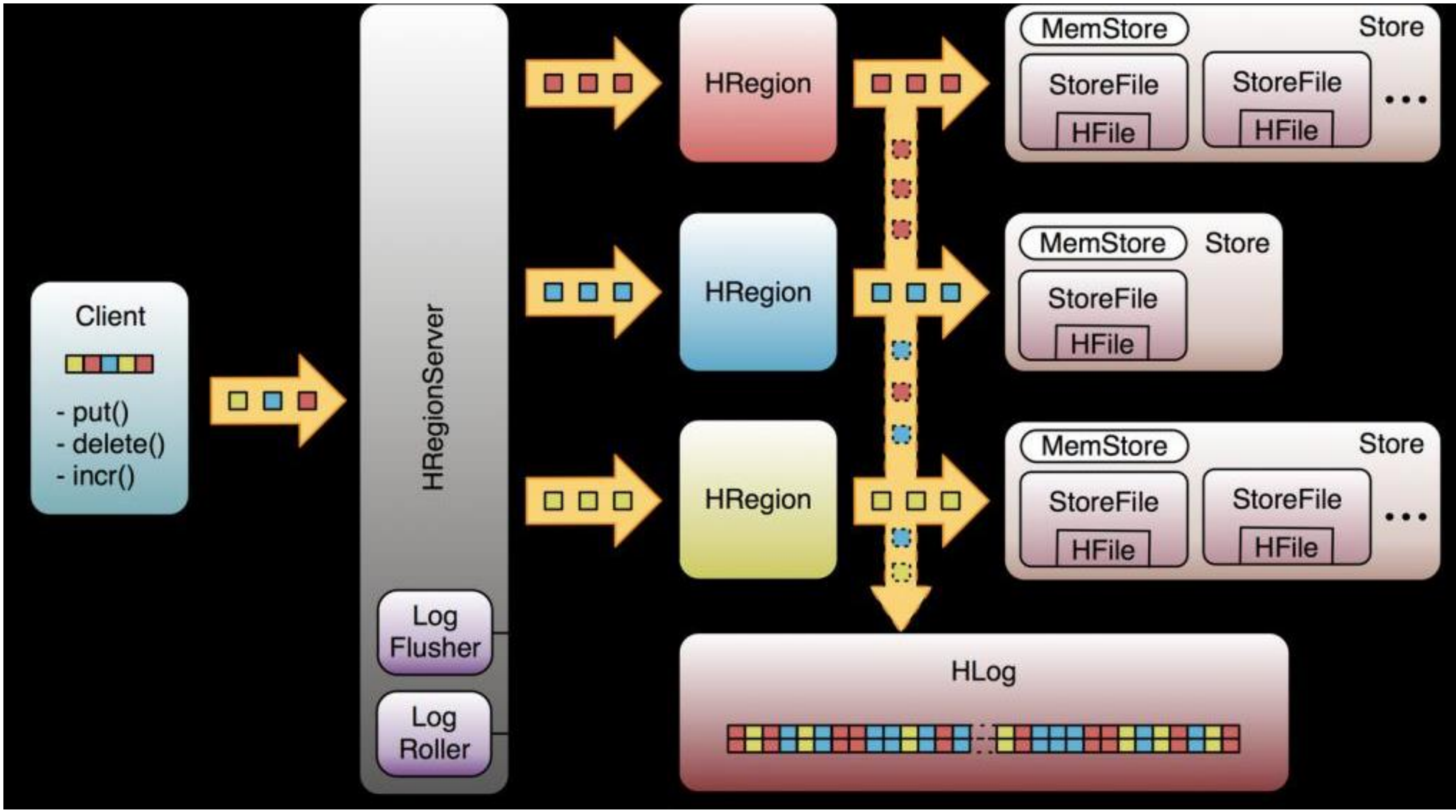
- OLAP query data based on timestamp of query submission from multi-versioning storage system
  - Modified HBase as storage
  - Mapreduce job for query execution
- Periodically materialize real-time data into data cube
  - Fully HBaseScan every time is time-consuming
    - Entire table is scanned & shuffled during MR
  - Streaming Mapreduce to maintain data cube

R-Store Architecture



- OLTP submitted to KV Store
- OLAP query processed by MapReduce
  - Scan on Hbase
- Refresh data cube through streaming MapReduce
- MetaStore to generate query timestamp T_Q & metadata (e.g. T_{DC})

Hbase in Short



Storage Design based on HBase

- Extend Scan to 2 versions
  - FullScan for querying data cube
  - IncrementalScan for querying real-time data
- Infinite versions of data to maintain query consistency
  - Compaction to remove stale versions
  - Global compaction
    - Immediately following data cube refresh
  - Local compaction
    - Compact old versions not accessed by any scan process

IncrementalScan in detail

- Target: Find out changes since last data cube materialization
- Method
  - Take 2 timestamps as input T_{DC} & T_Q, return the values with largest timestamp before T_{DC} & T_Q
- Implementations
  - Naïve: Accessing memstore & storefile in parallel
  - Adaptive: Maintain key modified since last materialization, first scan memstore, scan or random access keys based on cost

Compaction in detail

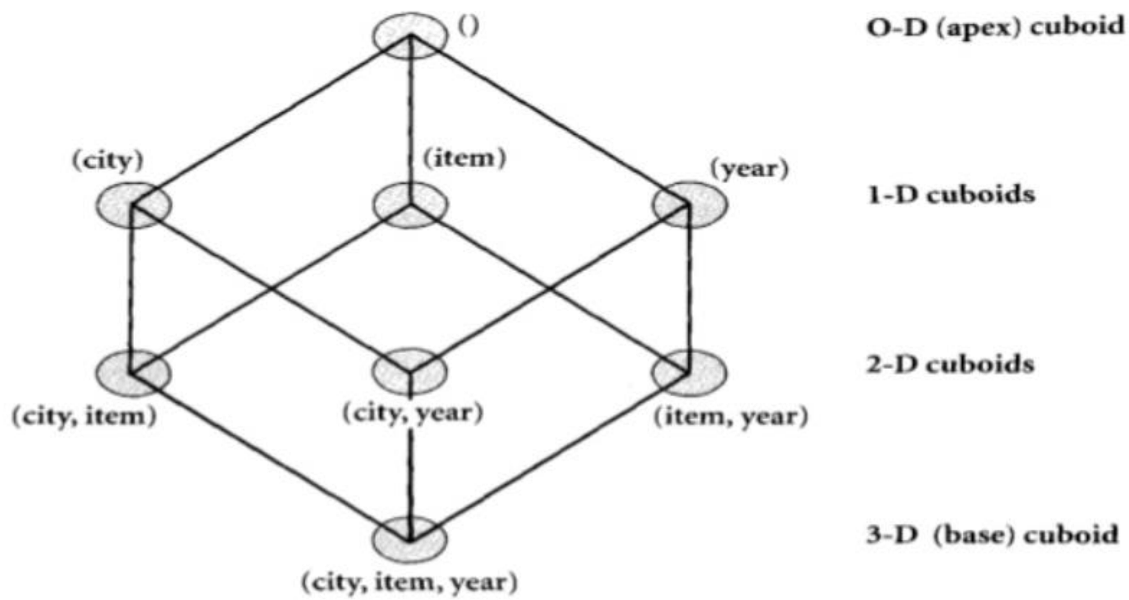
- Global compaction
  - Similar to Hbase's default, retain only one version of each key
  - Triggered by data cube's refresh completion
- Local compaction
  - Compacted data stored in different file in case block scan process
  - Files can be removed when not accessed by any scan
  - Triggered when #tuple/#key exceeds threshold

Data cube

Define a data cube for “Best Electronics”

Dimensions: city, item, year

Measure: Sales_in_dollars



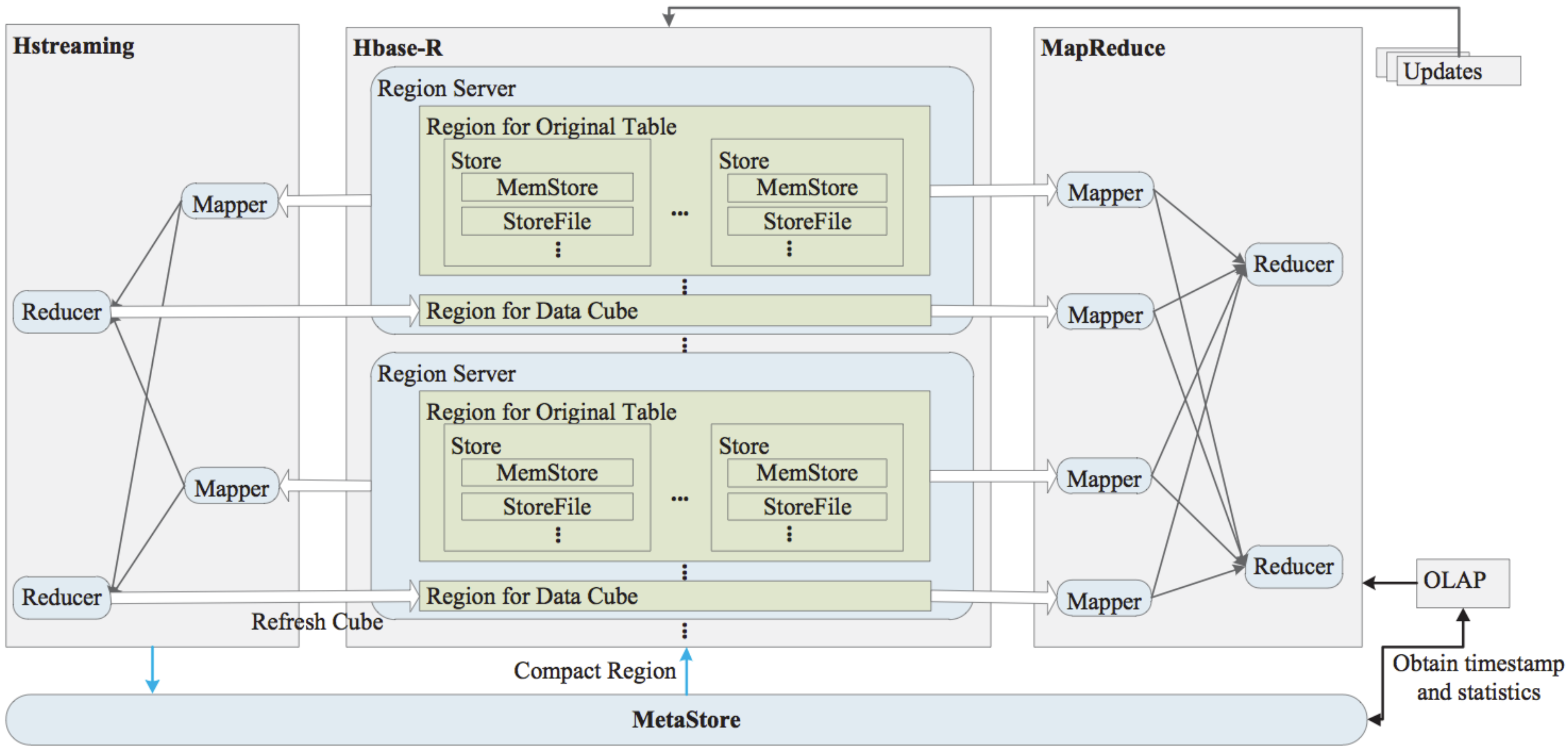
Data cube maintenance

- Re-computation
  - First run
  - FullScanon one region, generate a KV pair for each cuboid in mapper, aggregate & output in reducer
- Incremental Update
  - Consequent runs
  - Propagation step to computes change & update step to update cube
  - Streaming system updates cube inside & periodically materialize it into storage

HStreaming for cube maintenance

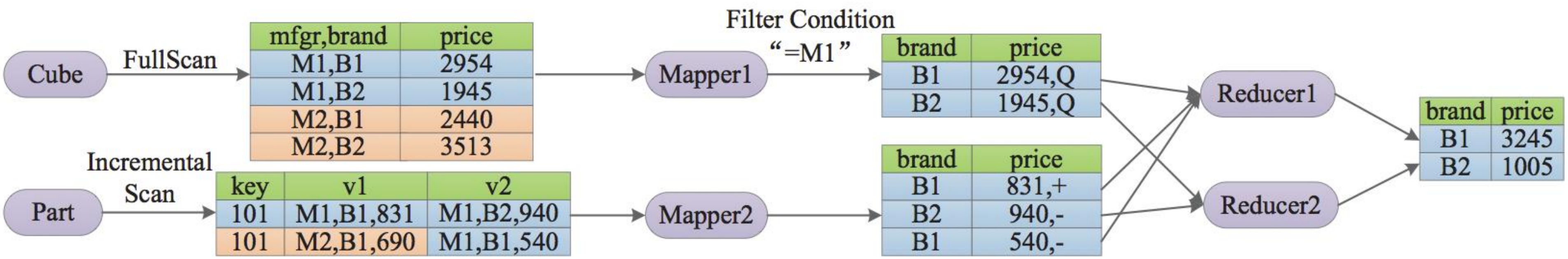
- Each mapper responsible for processing update within a key range
  - Maintain KVs locally, cache hot keys in memory
  - For updates, emit 2 KV pair for each cubiod(+, -)
- Reducer cache the output KV of mapper and invoke reduce every W_r, refresh cube every W_{cube}

Data Flow of R-Store



1. Updates arrives Hbase-R 2. stream updates to a Hstreaming mapper
3. Reducer periodically materialize local data cube to Hbase-R & notifies Metastore

RTOLAP query processing



Map

Tag the values with ‘Q’ ‘+’, ‘-’

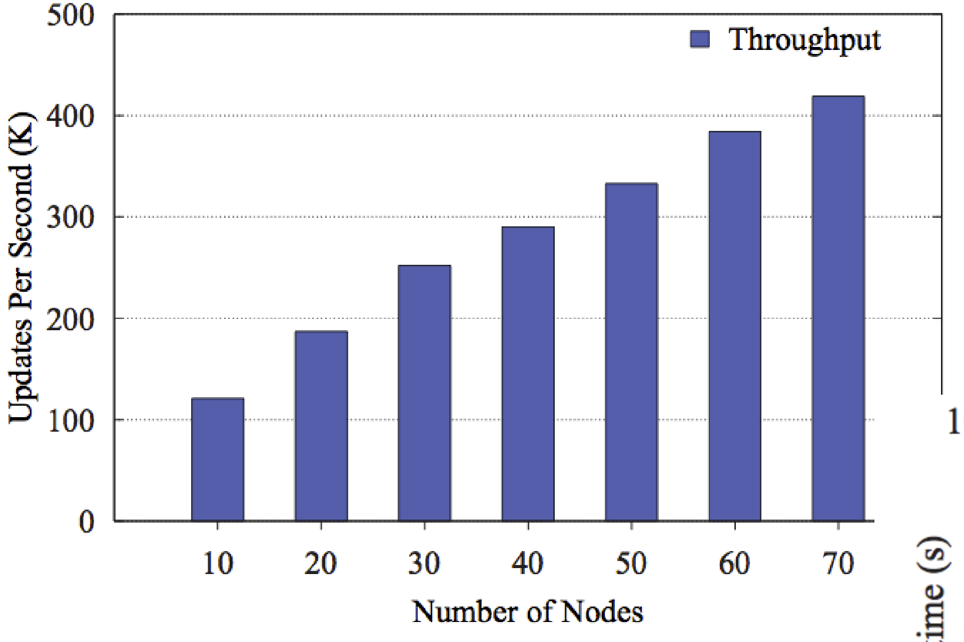
Reduce

Do calculation based on aggregation function & three values

Evaluation

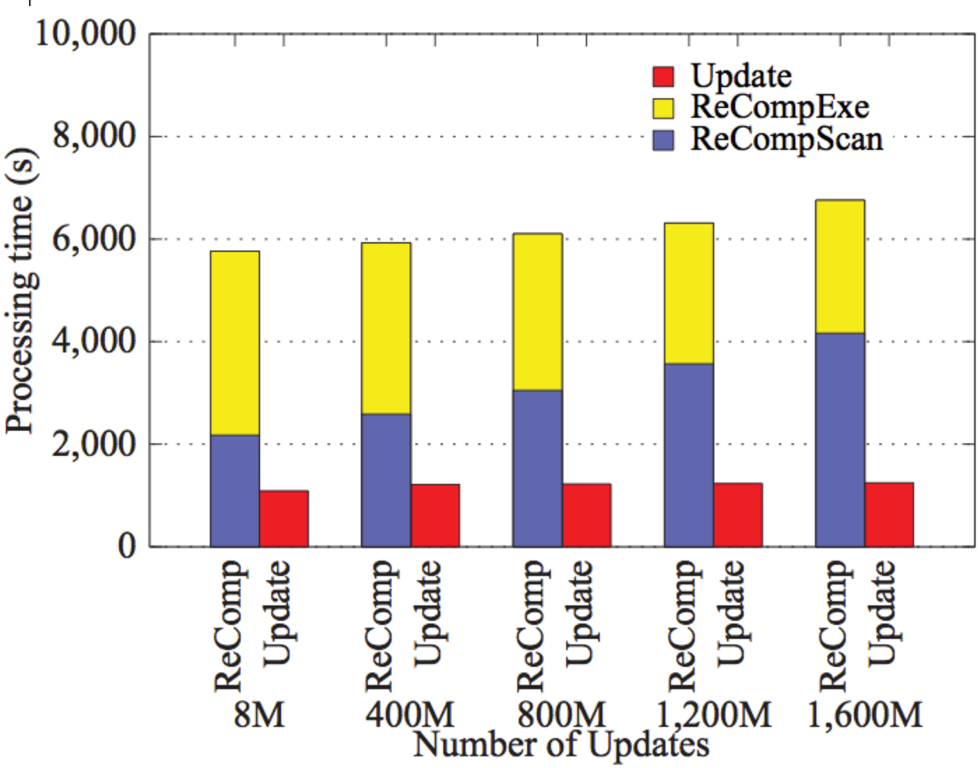
- Cluster of 144 nodes
  - Intel X3430 2.4 GHz processor
  - 8 GB of memory
  - 2x500 GB SATA disks
  - gigabit Ethernet
- TPC-H data

Performance of Maintaining Data cube

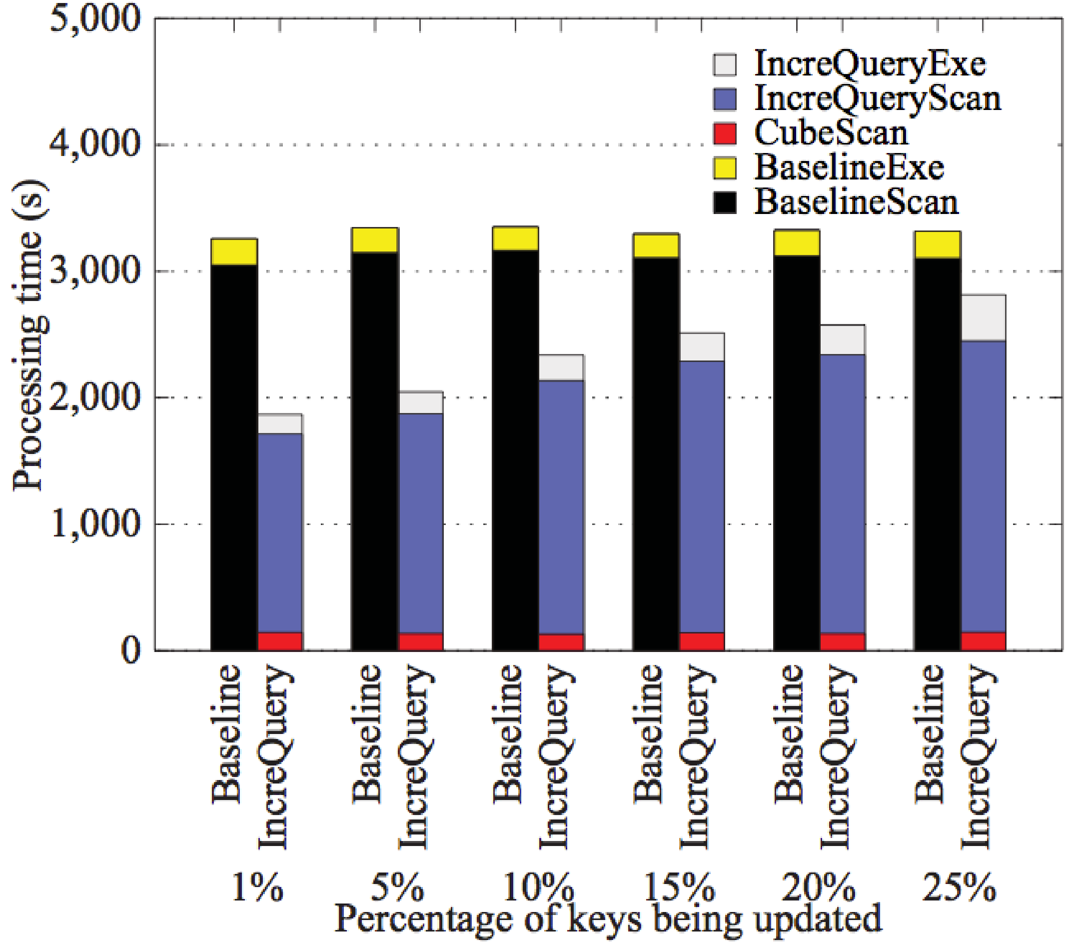


Hstreaming with 10 nodes have higher throughput than 40 Hbase-R nodes

1.6 billion keys, 1% updated, update algorithm fast enough, latency equals to Hbase-R input speed

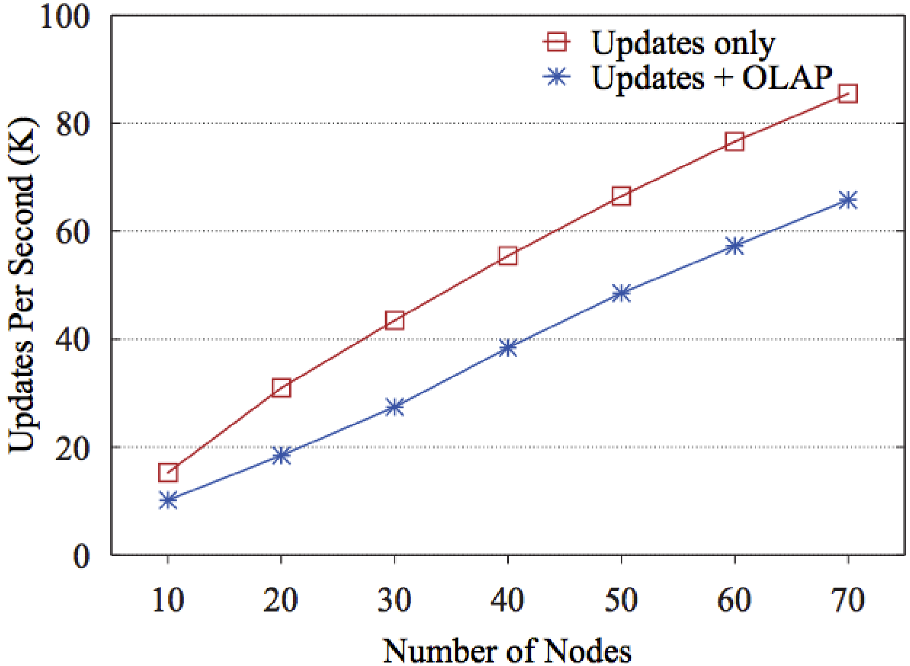


Performance of RT querying

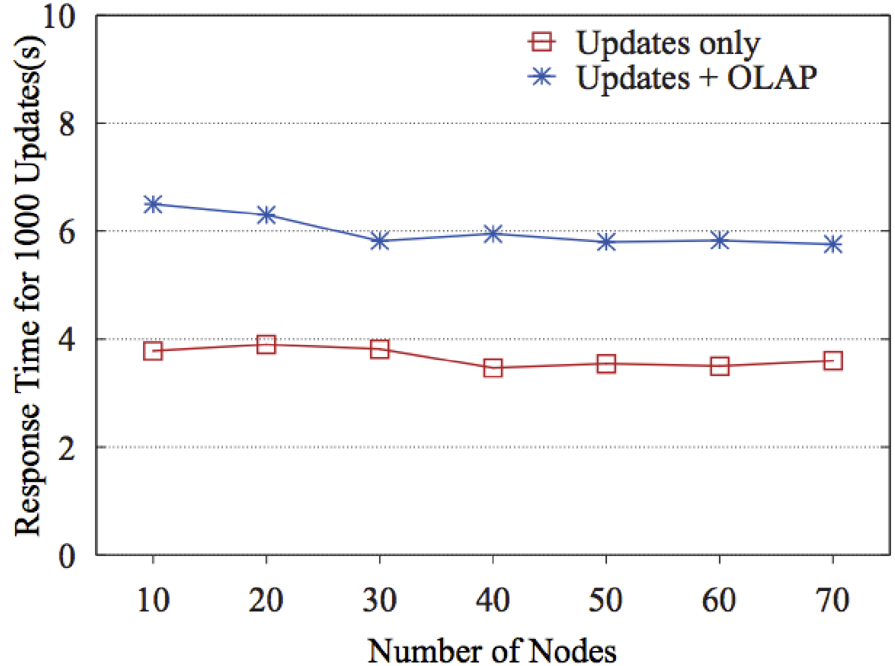


Small key range updates scans fewer data in Hbase-R, process fewer data

Performance of OLTP



(a) Throughput



(b) Latency

Related Work

- Database
  - C-Store(VLDB 05)
- Main-memory database
  - HyPer(ICDE 11), HYRISE(VLDB 10)
- Druid(SIGMOD 14)

Conclusion

- Multi-version concurrent control to support RTOLAP
- Data cube to reduce storage requirement & improve performance
- Streaming system to refresh data cube