NoSQL Concepts, Techniques & Systems – Part 2

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Outline

- NoSQL Systems - Types and Applications
- Dynamo
- HBase
- Hive
- Shark

RDBMS

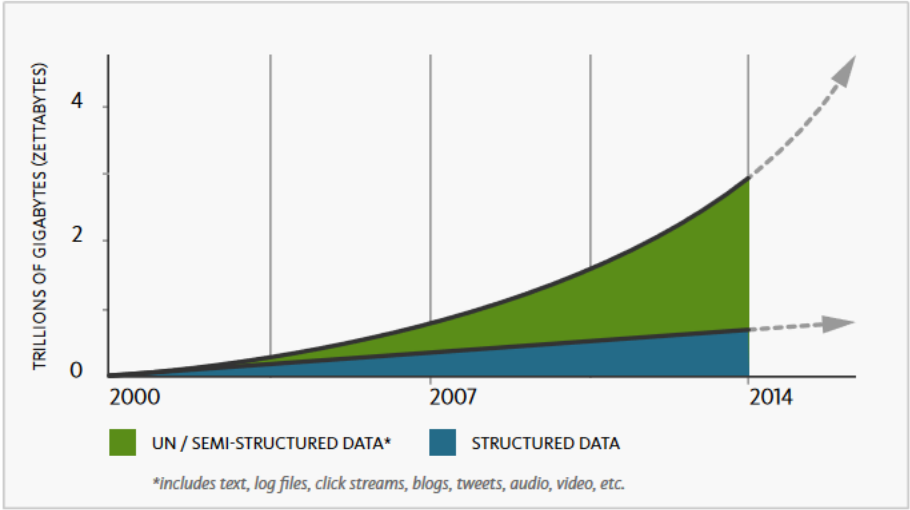
- Established technology
- Transactions support & ACID properties
- Powerful query language - SQL
- Experienced administrators
- Many vendors

Table: Item

item id	name	color	size
45	skirt	white	L
65	dress	red	M

But … – One Size Does Not Fit All[1]

- Requirements have changed:
  - Frequent schema changes, management of unstructured and semi-structured data
  - Huge datasets
  - High read and write scalability
  - RDBMSs are not designed to be
    - distributed
    - continuously available
  - Different applications have different requirements[1]



[1] "One Size Fits All": An Idea Whose Time Has Come and Gone https://cs.brown.edu/~ugur/fits_all.pdf
Figure from: http://www.couchbase.com/sites/default/files/uploads/all/whitepapers/NoSQL-Whitepaper.pdf

NoSQL (not-only-SQL)

- A broad category of disparate solutions
- Simple and flexible non-relational data models
  - schema-on-read vs schema-on-write
- High availability & relax data consistency requirement (CAP theorem)
  - BASE vs ACID
- Easy to distribute – horizontal scalability
  - data are replicated to multiple nodes
- Cheap & easy (or not) to implement (open source)

Distributed (Data Management) Systems

- Number of processing nodes interconnected by a computer network
- Data is stored, replicated, updated and processed across the nodes
- Networks failures are given, not an exception
  - Network is partitioned
  - Communication between nodes is an issue

  → Data consistency vs Availability

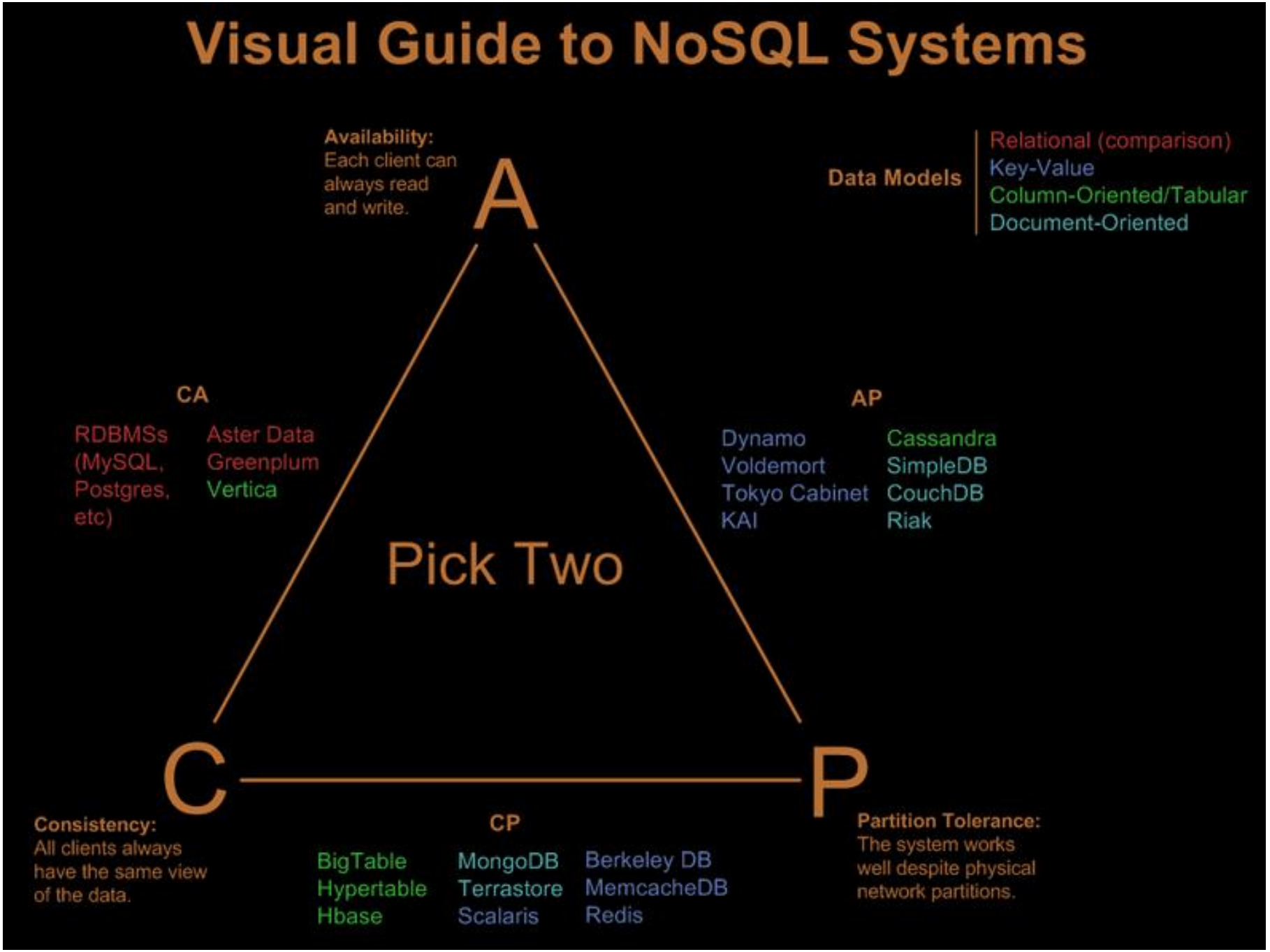


figure from http://blog.nahurst.com/visual-guide-to-nosql-systems

NoSQL Systems – Types and Applications

NoSQL Classification Dimensions[HBase]

- **Data model** – how the data is stored; does it evolve
- **Storage model** – in-memory vs persistent
- **Consistency model** – strict, eventual consistent, etc.
  - Affects reads and writes requests
- **Physical model** – distributed vs single machine
- Re**ad/Write performance** – what is the proportion between reads and writes
- **Secondary indexes** - sort and access tables based on different fields and sorting orders

NoSQL Classification Dimensions[HBase]

- **Failure handling** – how to address machine failures
- **Compression** – result in substantial savings in raw storage
- **Load balancing** – how to address high read or write rate
- **Atomic read-modify-write** – difficult to achieve in a distributed system
- **Locking, waits and deadlocks** – locking models and version control

NoSQL Data Models

- Key-Value Stores
- Document Stores
- Column-Family Stores
- Graph Databases

- Impacts application, querying, scalability

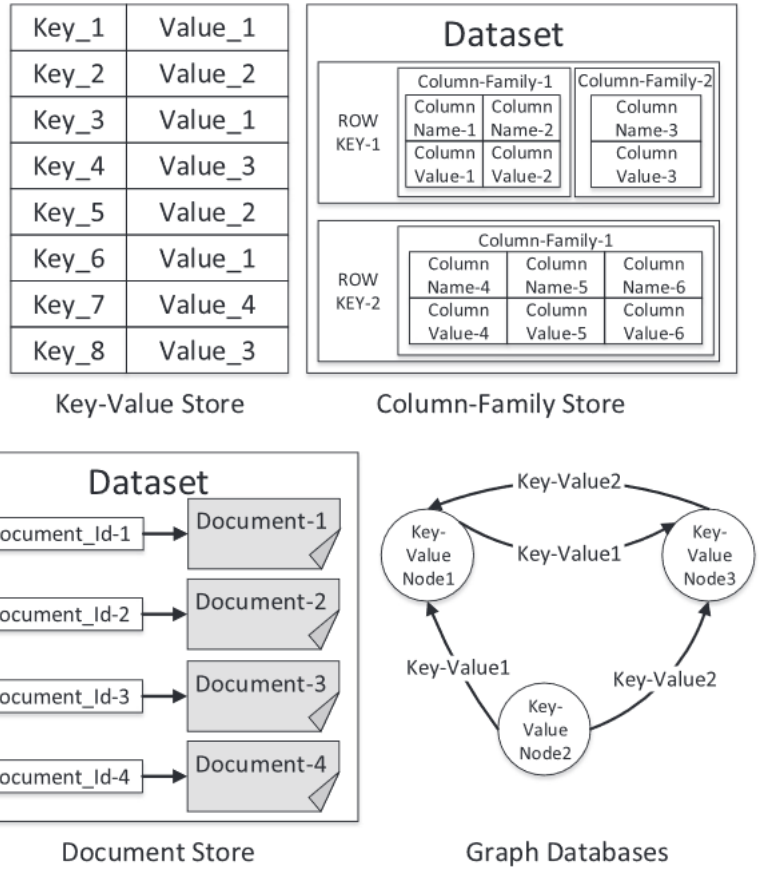


figure from [DataMan]

DBs not referred as NoSQL

- Object DBs
- XML DBs
- Special purpose DBs
  - Stream processing

Key-Value Stores[DataMan]

- Schema-free
  - Keys are unique
  - Values of arbitrary types
- Efficient in storing distributed data
- (very) Limited query facilities and indexing
  - get(key), put(key, value)
  - Value → opaque to the data store → no data level querying and indexing

Key_1	Value_1
Key_2	Value_2
Key_3	Value_1
Key_4	Value_3
Key_5	Value_2
Key_6	Value_1
Key_7	Value_4
Key_8	Value_3

Key-Value Store

Key-Value Stores[DataMan]

- Types
  - In-memory stores – Memcached, Redis
  - Persistent stores – BerkeleyDB, Voldemort, RiakDB

Key_1	Value_1
Key_2	Value_2
Key_3	Value_1
Key_4	Value_3
Key_5	Value_2
Key_6	Value_1
Key_7	Value_4
Key_8	Value_3

Key-Value Store

- Not suitable for
  - structures and relations
  - accessing multiple items (since the access is by key and often no transactional capabilities)

Key-Value Stores[DataMan]

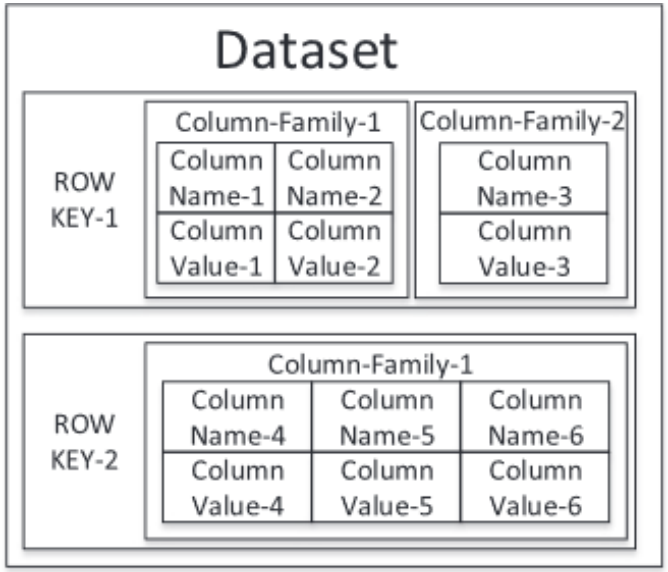
Key_1	Value_1
Key_2	Value_2
Key_3	Value_1
Key_4	Value_3
Key_5	Value_2
Key_6	Value_1
Key_7	Value_4
Key_8	Value_3

Key-Value Store

- Applications:
  - Storing web session information
  - User profiles and configuration
  - Shopping cart data
  - Using them as a caching layer to store results of expensive operations (create a user-tailored web page)

Column-Family Stores[DataMan]

- Schema-free
  - Rows have unique keys
  - Values are varying column families and act as keys for the columns they hold
  - Columns consist of key-value pairs

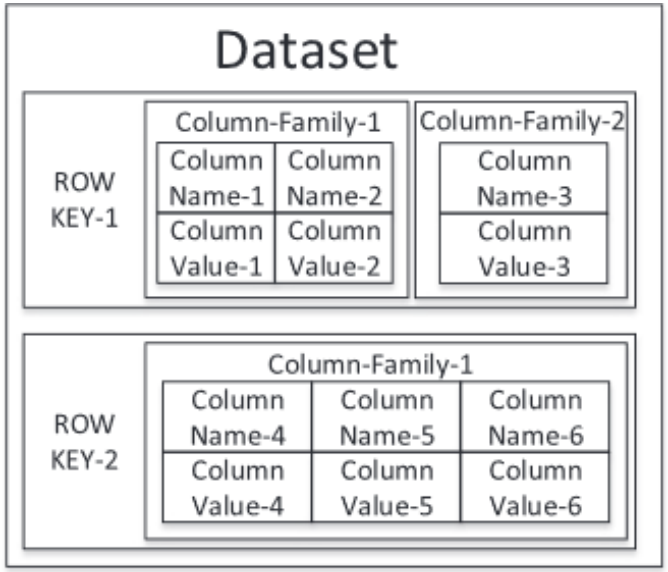


Column-Family Store

- Better than key-value stores for querying and indexing

Column-Family Stores[DataMan]

- Types
  - Googles BigTable, Hadoop HBase
  - No column families – Amazon SimpleDB, DynamoDB
  - Supercolumns - Cassandra

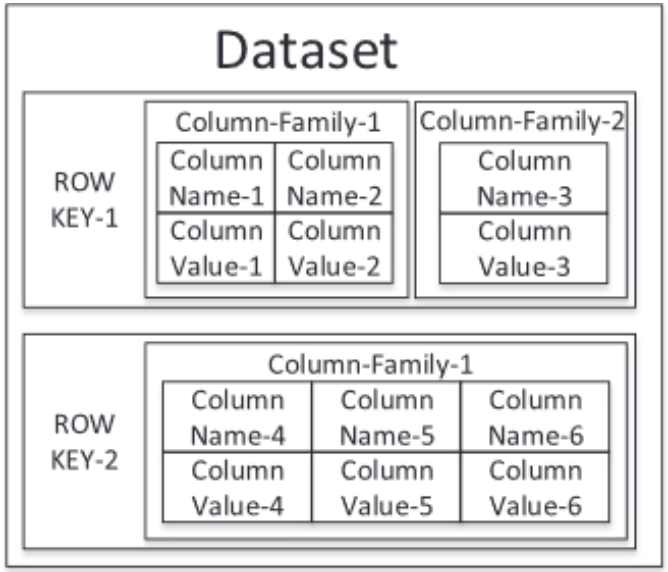


Column-Family Store

- Not suitable for
  - structures and relations
  - highly dynamic queries (HBase and Cassandra)

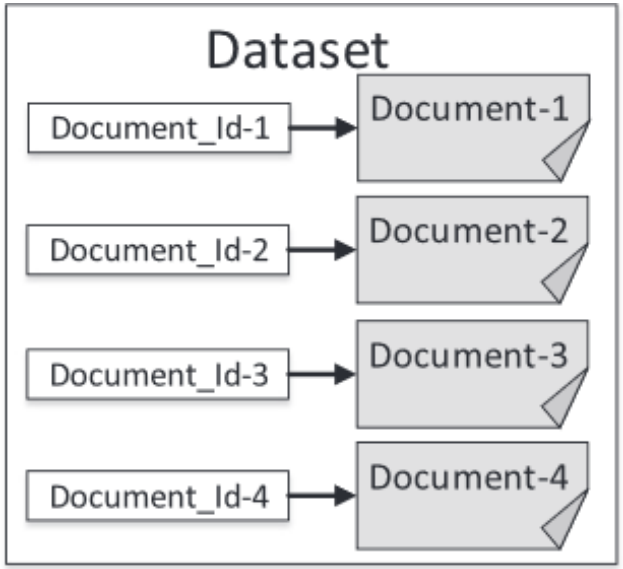
Column-Family Stores[DataMan]

- Applications:
  - Document stores applications
  - Analytics scenarios – HBase and Cassandra
    - Web analytics
    - Personalized search
    - Inbox search



Column-Family Store

Document Stores[DataMan]

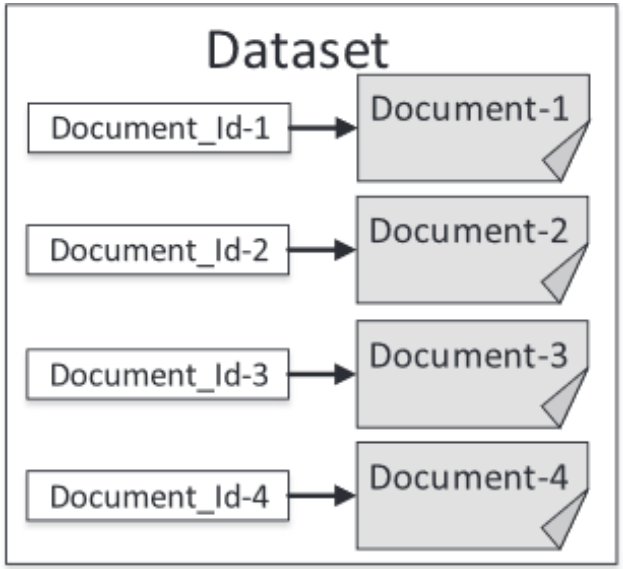


Document Store

- Schema-free
  - Keys are unique
  - Values are documents – complex (nested) data structures in JSON, XML, binary (BSON), etc.
- Indexing and querying based on primary key and content
- The content needs to be representable as a document
- MongoDB, CouchDB, Couchbase

Document Stores[DataMan]

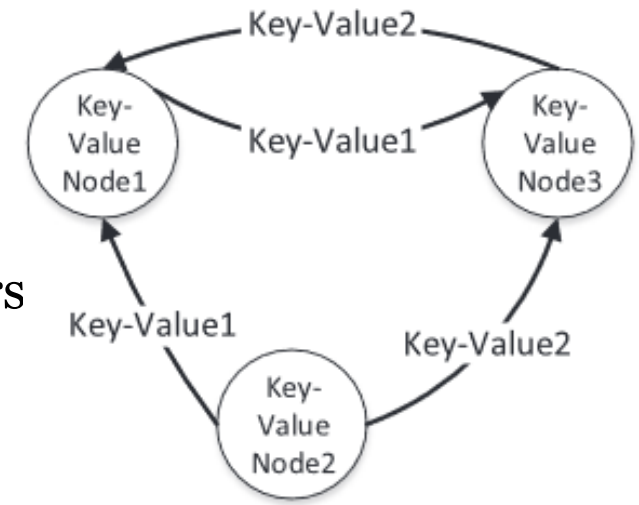
- Applications:
  - Items with similar nature but different structure
  - Blogging platforms
  - Content management systems
  - Event logging
  - Fast application development



Document Store

Graph Databases[DataMan]

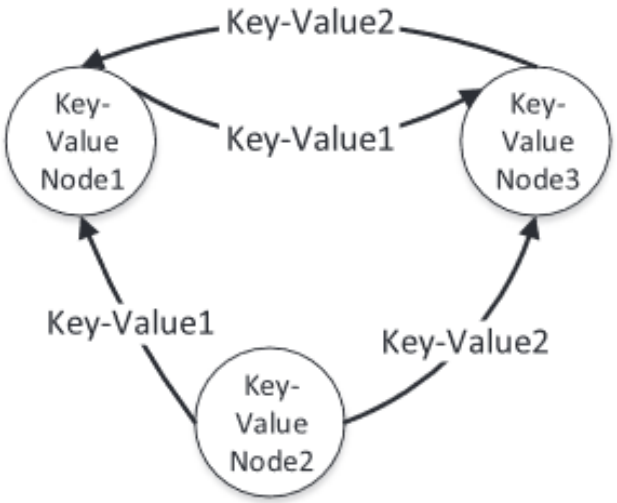
- Graph model
  - Nodes/vertices and links/edges
  - Properties consisting of key-value pairs
- Suitable for very interconnected data since they are efficient in traversing relationships
- Not as efficient
  - as other NoSQL solutions for non-graph applications
  - horizontal scaling
- Neo4J, HyperGraphDB



Graph Databases

Graph Databases[DataMan]

- Applications:
  - location-based services
  - recommendation engines
  - complex network-based applications
    - social, information, technological, and biological network
  - memory leak detection



Graph Databases

Multi-model Databases

- … but one application can actually require different data models for the different data it stores
- Provide support for multiple data models against a single backend:
  - OrientDB supports key-value, document, graph & object models; geospatial data;
  - ArangoDB supports key-value, document & graph models stored in JSON; common query language;
- How to query the different models in a uniform way

Big Data Analytics Stack

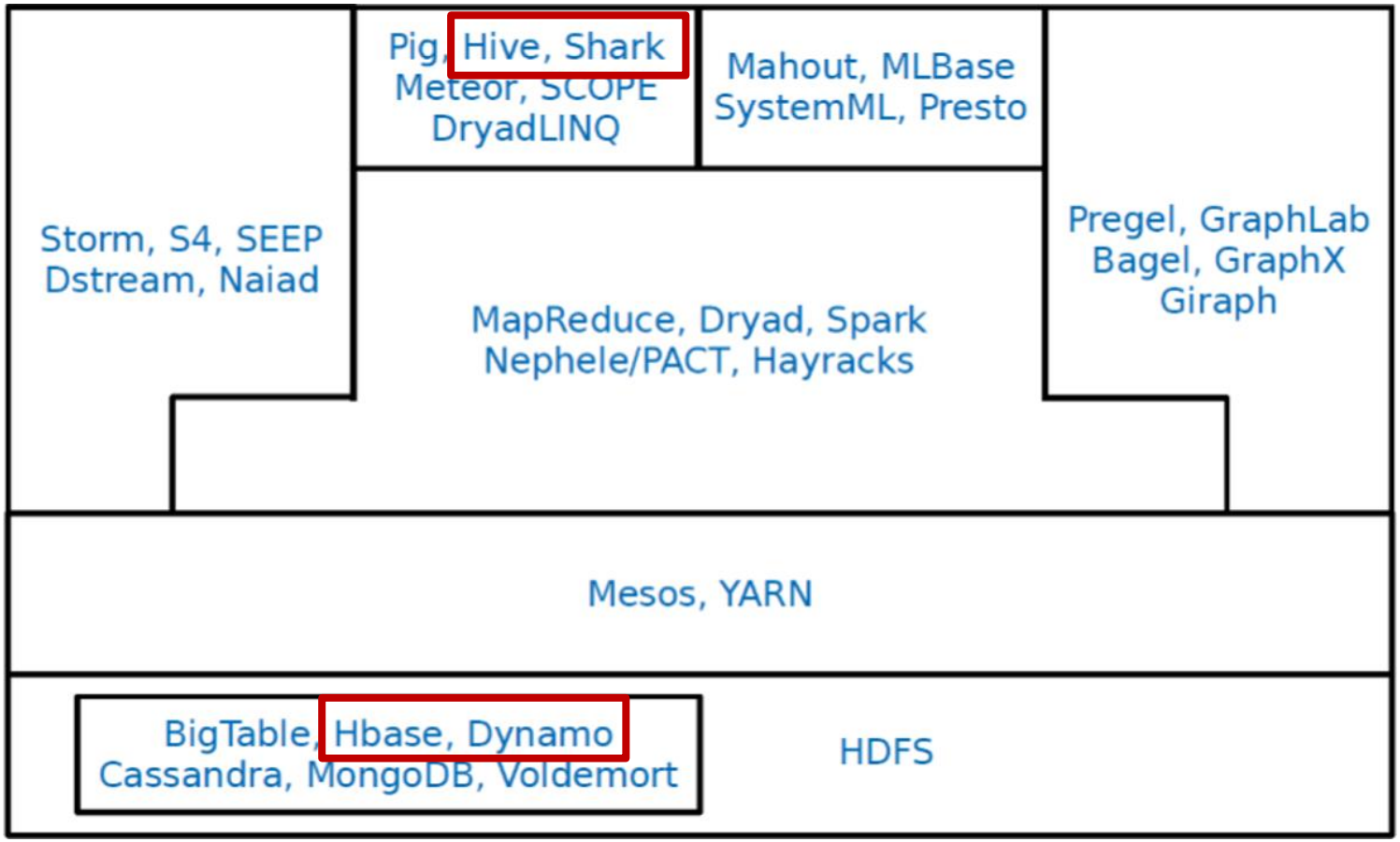
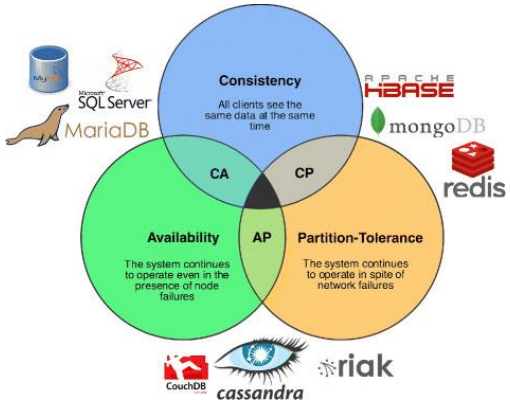


figure from: https://www.sics.se/~amir/dic.htm

Dynamo[Dynamo]

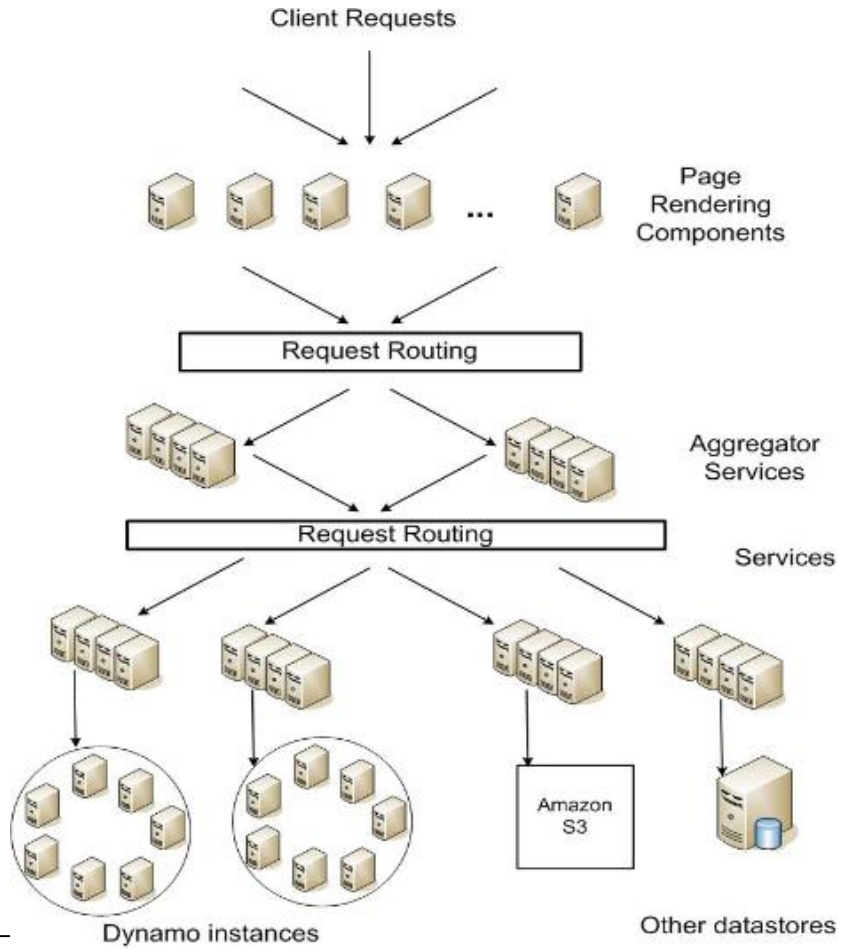
Dynamo



- Highly-available key-value store
- CAP: Availability and Partition Tolerance
- Use case: customer should be able to view and add to the shopping cart during various failure scenarios
  - always serve writes and reads
- Many Amazon services only need primary-key access
  - Best seller lists
  - Customer preferences
  - Product catalog

Amazon's Service Oriented Architecture

- Example: a single page is rendered employing the responses from over 150 services



Why not RDBMS?

- Amazon's services often store and retrieve data only by key
  - thus do not need complex querying and managing functionalities
- Replication technologies usually favor consistency, not availability
- Cannot scale out easily

Dynamo[Dynamo]

- Storage system requirements:
  - Query model
    - put and get operations to items identified by key
    - binary objects, usually < 1MB
  - ACID-compliant systems have poor availability but Dynamo applications
    - does not require isolation guarantees
    - permits only single key updates

Dynamo[Dynamo]

- System requirements:
  - Efficiency
    - Runs on commodity hardware with Amazon's services having stringent latency requirements
  - No security related requirements

Dynamo[Dynamo]

- Design considerations
  - When to resolve conflicting updates
    - Reads or writes – never reject writes
  - Who resolves conflicting updates
    - Data store or application
  - Incremental scalability
  - Symmetry
  - Decentralization
  - Heterogeneity

Dynamo - Techniques

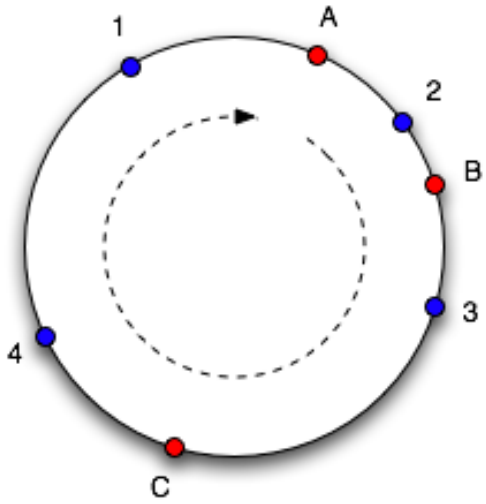
- Consistent hashing
- Quorum-like techniques
- Object versioning & vector clocks

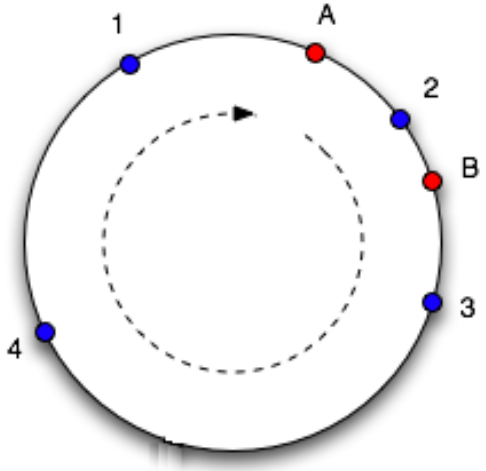
NoSQL: Techniques – Consistent Hashing [Karger]

Basic idea:

- arrange the nodes in a ring
- include hash values of all nodes in hash structure
- calculate hash value of the key to be added/retrieved
- choose node which occurs next clockwise in the ring
- if node is dropped or gets lost, missing data is redistributed to adjacent nodes
- if a new node is added, its hash value is added to the
- the hash realm is repartitioned, and hash data will be transferred to new neighbor

→ no need to update remaining nodes!





Dynamo[Dynamo]

- 128-bit identifier is generated by hashing the key to identify storage node
- Challenges in the basic algorithm
  - Non-uniform data and load distribution
  - Heterogeneity is not accounted for
- Virtual nodes
  - Looks like a single node in the system, but each node can be responsible for more than one virtual node.

Dynamo[Dynamo]

- Each data item is replicated on N hosts
- Each key is assigned to a coordinator node
  - Handles read or write operations

- Preference list contains > N nodes
  - List of nodes responsible for storing the value for a particular key, known by every node
  - Constructed by skipping positions in the ring
  - Nodes in different data centers

Dynamo[Dynamo]

- System architecture
  - get(key) and put(key, context, object)
    - Context stores the object version
  - Quorum protocol – N, W, R
    - N – number of nodes that store replicas
    - R – number of nodes for a successful read
    - W – number of nodes for a successful write
    - R + W > N strong consistency
      - Latency of get (or put) depends on the slowest node
    - R + W ≤ N eventual consistency – better latency

Dynamo[Dynamo]

- get(key) and put(key, context, object)
  - Context stores the object version
- Coordinator node handles reads and writes
  - put() - generates a vector clock and sends to N nodes
  - get() - requests all existing version and returns all causality **unrelated** to the client
    - The divergent versions are then reconciled and the reconciled version superseding the current versions is written back.

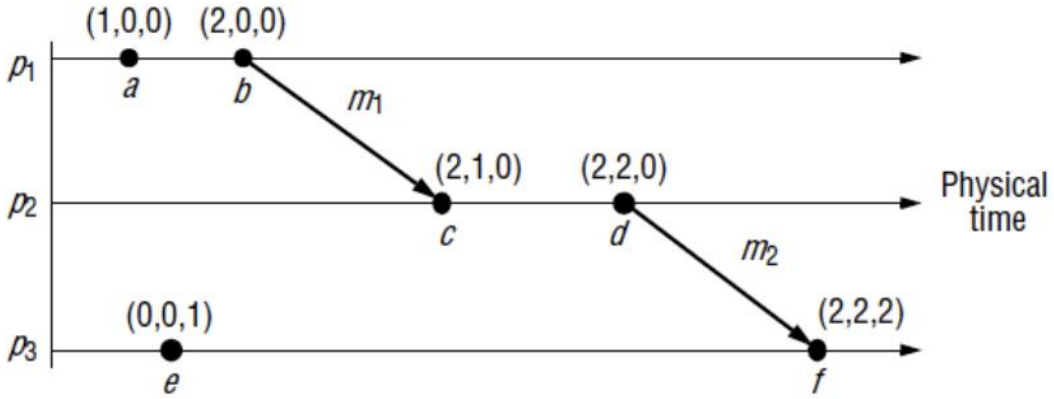
NoSQL: Techniques – Vector Clock[Coulouris]

- A vector clock for a system of N nodes is an array of N integers.
- Each process keeps its own vector clock, V_i , which it uses to timestamp local events.
- Processes piggyback vector timestamps on the messages they send to one another, and there are simple rules for updating the clocks

two events e and e': that $e \rightarrow e' \leftrightarrow V(e) < V(e')$

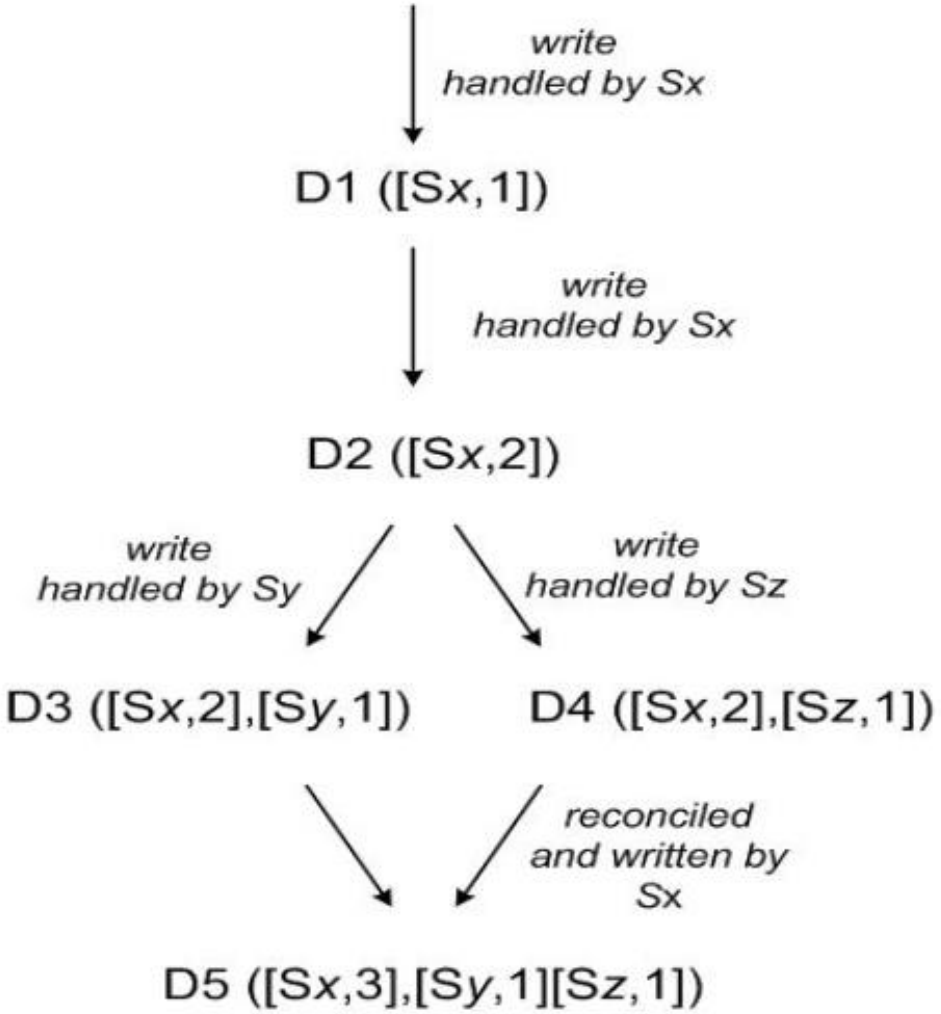
$c \parallel e$ since neither $V(c) \leq V(e)$ nor $V(e) \leq V(c)$

c & e are concurrent



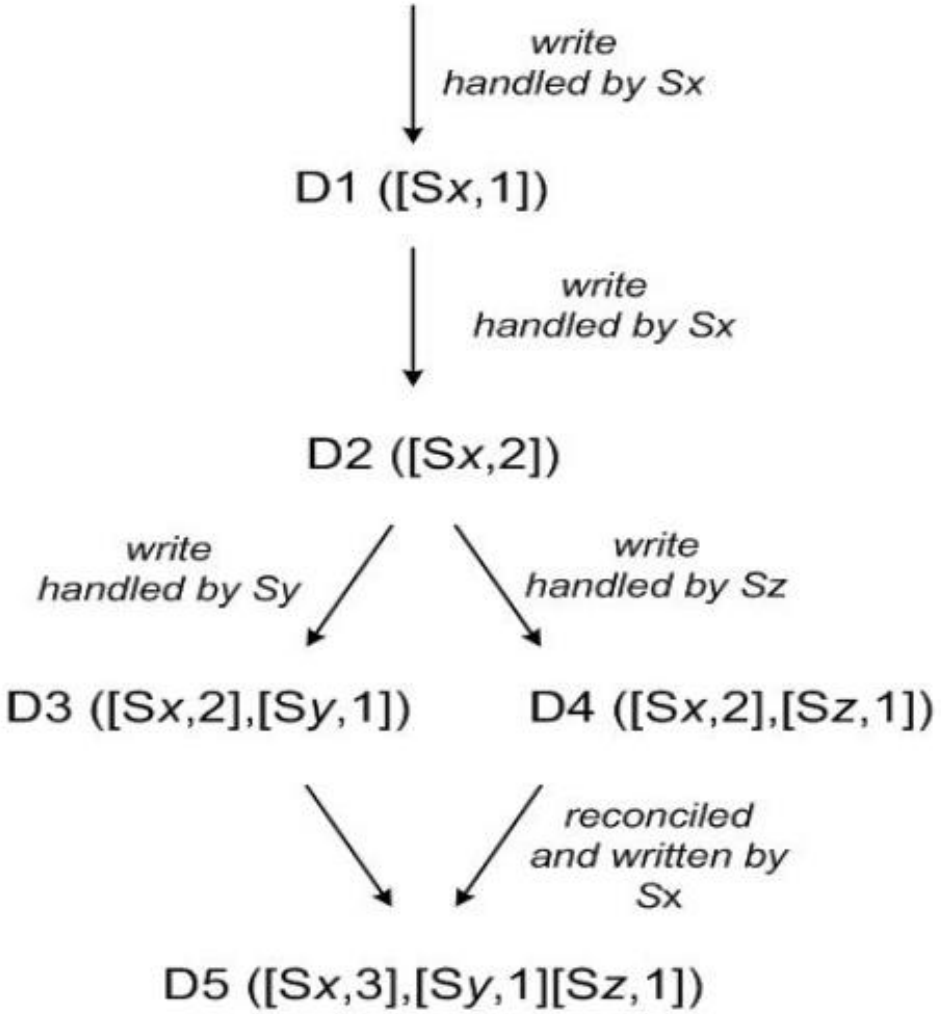
Dynamo - Versioning

- Asynchronous update propagation
- Use case: shopping cart
- Each update is a new, immutable version --> many versions of an object may exist
- Replicas eventually become consistent



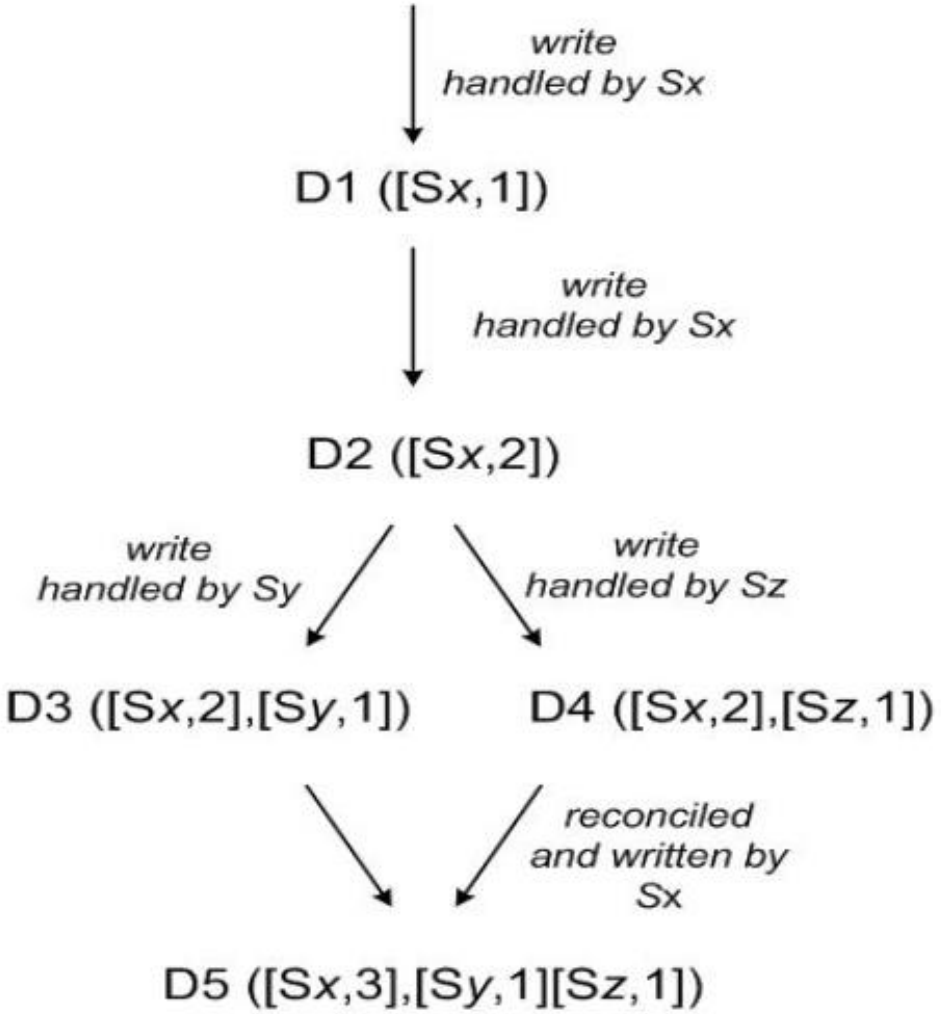
Dynamo - Versioning

- Reconciliation
  - Syntactic
  - Semantic
- Vector clocks
  - Client specifies which version is updating
  - All leave objects are returned if syntactic reconciliation fails



Dynamo - Versioning

- Sx, Sy, Sz – nodes
- D1, D2, D3, D4, D5 – versions of data items
- [Sx, 1] vector clock at Sx
- Divergent versions are rare
  - One version: 99.94%
  - Four versions: 0.00009%



Dynamo[Dynamo]

- Handling failure – hinted handoff
- Sloppy quorum - all read and write operations are performed on the first N healthy nodes from the preference list
  - If a node is temporary down the replica is sent to another
  - The replica will have a hint in its metadata for its intended location
  - After the node recovers it will receive the replica

Dynamo - Summary

- Highly-available key-value store
- CAP: Sacrifices consistency for availability in the pretense of network partitions
- Every node has the same responsibilities
- Consistent hashing
- Vector clocks for replicas reconciliation
- Quorum-like and decentralized replica synchronization protocol

HBase[HBase][Hadoop]

Column-oriented Databases

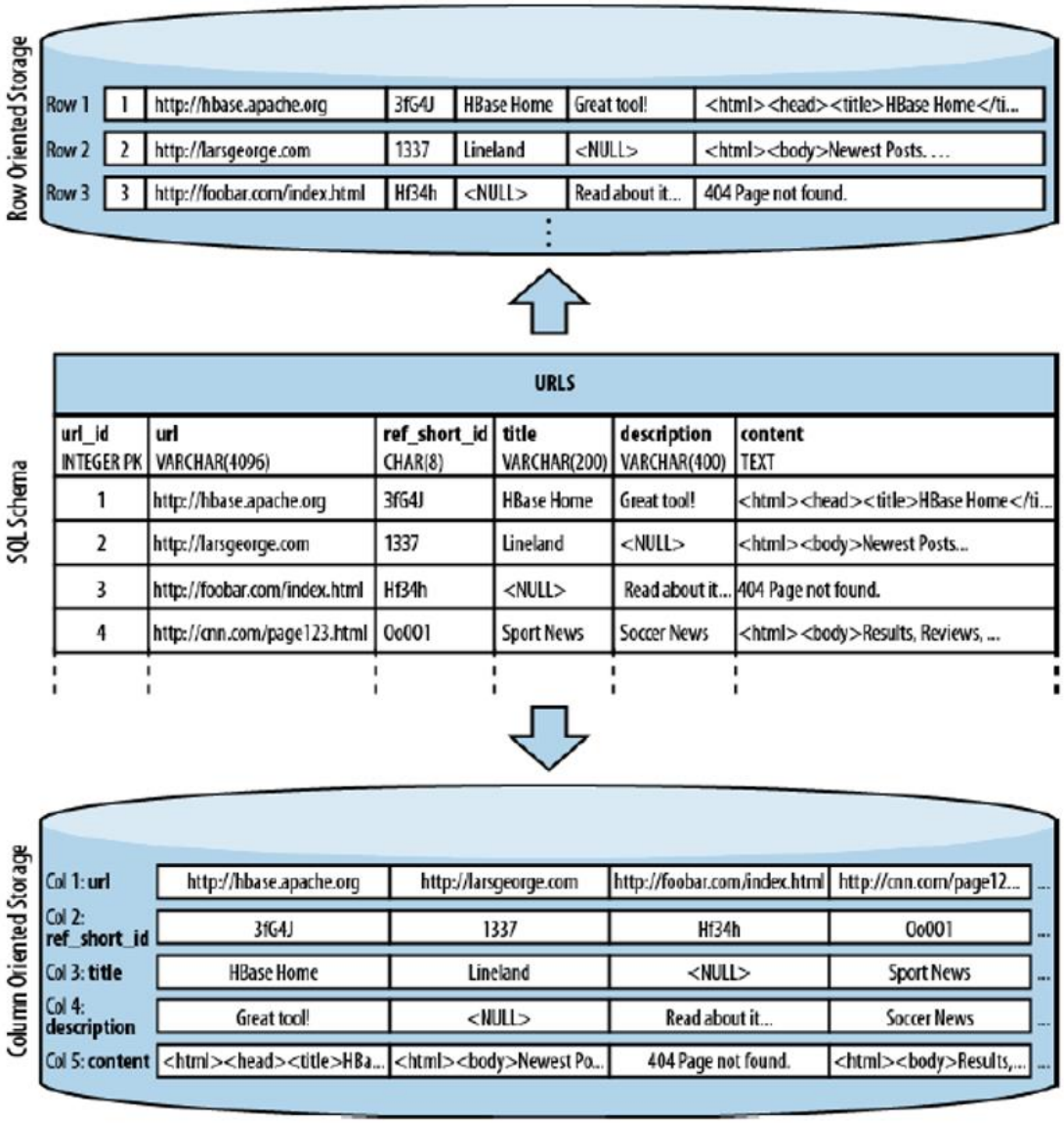
- Saved data grouped by columns
- Not all values are needed for some queries/applications
  - Analytical databases
- Leads to
  - Reduced I/O
  - Better compression due to similar values

Column-oriented Model[HBase]

Row-oriented storage

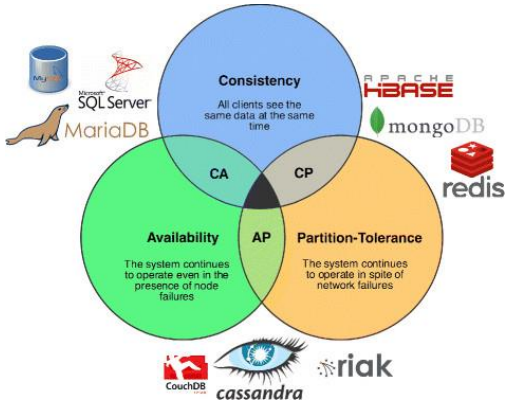
SQL Schema

Column-oriented storage (HBase)



HBase – a Column-family Database

- Column-family store; hosts very large sparse tables
- Based on Google BigTable and built on top of HDFS
- Provide l*ow-latency* real-time read/write random access on a (sequence of) cell level
- Scales linearly on commodity hardware
- Atomic access to row data
- CAP: provides strong consistency and partition tolerance
  → all writes on the primary replica



HBase[HBase] Canonical Example – *webtable*

Row key	Time stamp	Family `content`		Family `outgoing links`		Family `inbound links`	
		html	**png**	**cnnsi.com**	**my.look.ca**	**news.bbc.com**	**theguardian.com**
com.cnn.www	t9			CNN	cnn.com	cnn.com	cnn.com
	t8		logo.png				
	t6	contents:html = "<html>…"	logo1.png				
	t5	contents:html = "<html>…"					
	t3	contents:html = "<html>…"					

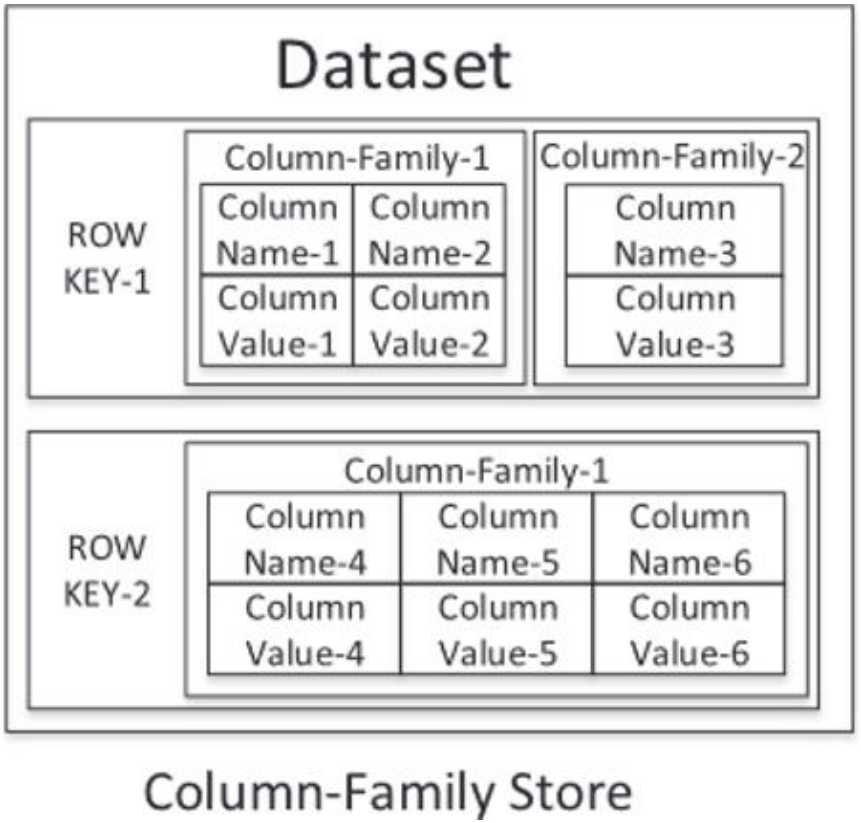
HBase in Facebook[HBaseInFacebook]

- Facebook applications that use HBase with HBase enhancements performed internally in Facebook
  - Facebook Messaging - High write throughput
  - Facebook Insights – Real-time analytics
  - Facebook Metric System - Fast reads of recent data and table scans

- Others: Adobe, StumbleUpon, Twitter, Yahoo!

HBase[HBase]

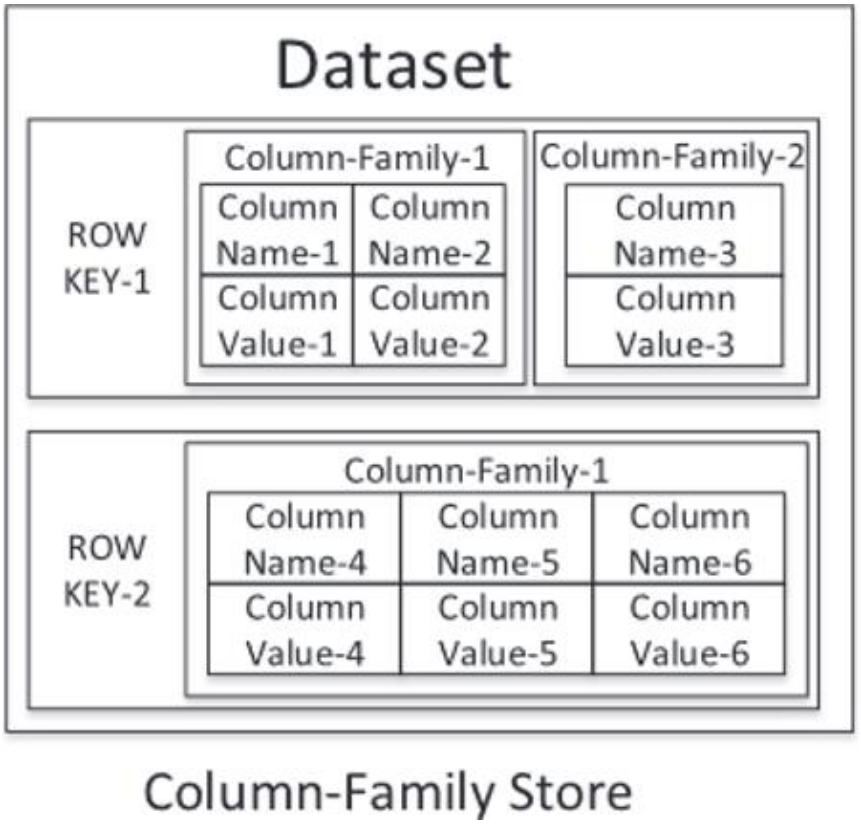
- Terminology overlaps, but misleading:
  - *Most basic unit* Column
    - versions
  - Row
  - Table
  - Cell



HBase[HBase]

- A **table** consists of multiple rows
  - primary key access
- A **row** has a key and column families:
  - Atomic access to row data
  - Sorted lexically:

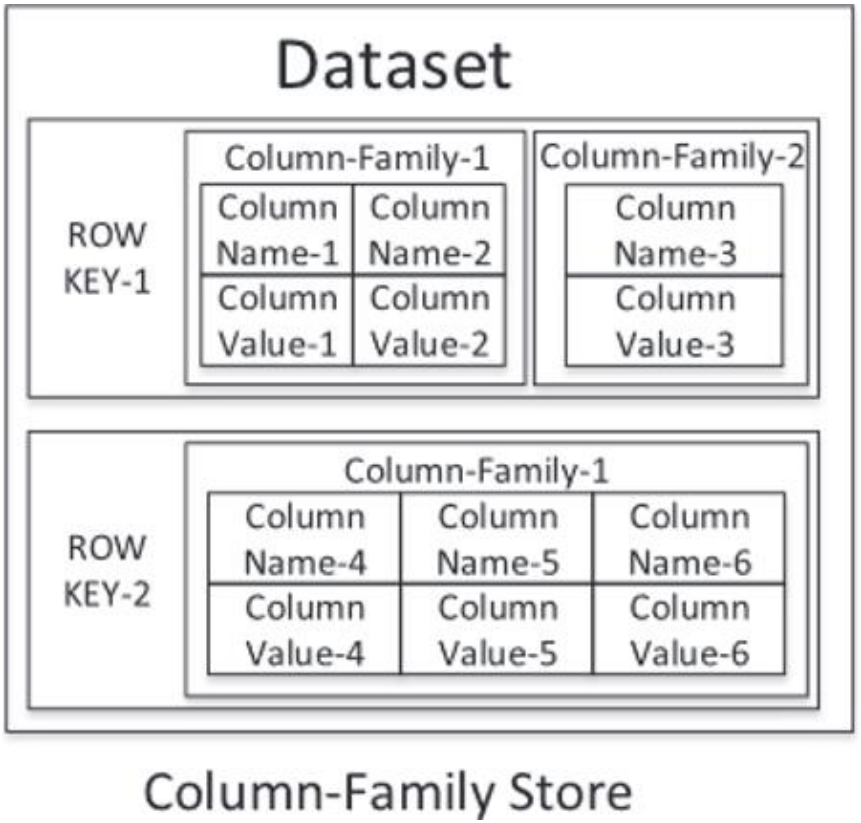
    r1
    r10
    r11
    r2



Column-Family Store

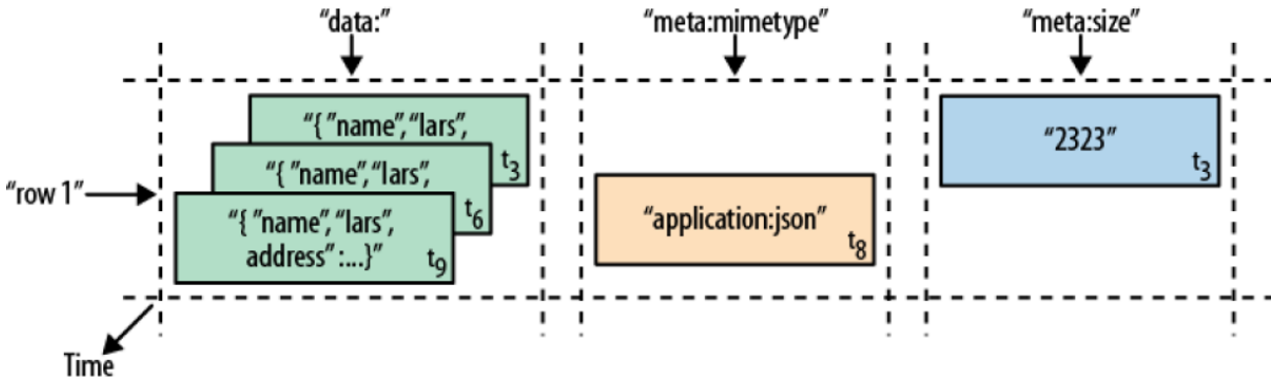
HBase[HBase]

- Columns Families: `content`
- Columns: *family:qualifier*
  `content:pdf`
  `content:html`
- All columns in a column family stored together in HFile



HBase – Cell [HBase]

- Cell contains value and timestamp
  - `(Table, RowKey, Family, Column, Timestamp) → Value`



Row Key	Time Stamp	Column "data:"	Column "meta:" "mimetype"	Column "meta:" "size"	Column "counters:" "updates"
"row1"	t_3	"{ "name" : "lars", "address" : ...}"		"2323"	"1"
	t_6	"{ "name" : "lars", "address" : ...}"			"2"
	t_8		"application/json"		
	t_9	"{ "name" : "lars", "address" : ...}"			"3"

HBase[HBase]

- Canonical example – *webtable*

Row key	Time stamp	Family `content`		Family `outgoing links`		Family `inbound links`	
		html	**png**	**cnnsi.com**	**my.look.ca**	**news.bbc.com**	**theguardian.com**
com.cnn.europe	t9			CNN	cnn.com	cnn.com	cnn.com
	t8		logo.png				
	t6	contents:html = "<html>…"	logo1.png				
	t5	contents:html = "<html>…"					
com.cnn.asia	t8	contents:html = "<html>…"					

HBase - Summary

- Column-oriented data store
  - Hosts very large sparse tables on commodity hardware
  - Column values are timestamped
- Low-latency real-time random access on HDFS!
  - blog.cloudera.com/blog/2012/06/hbase-io-hfile-input-output/
- Row are sorted & stored lexicographically
  - Atomic access to row data
    - But no transactional features across multiple rows
  - No real indexes & high write throughput
- Canonical application - webtable

Big Data Analytics Stack

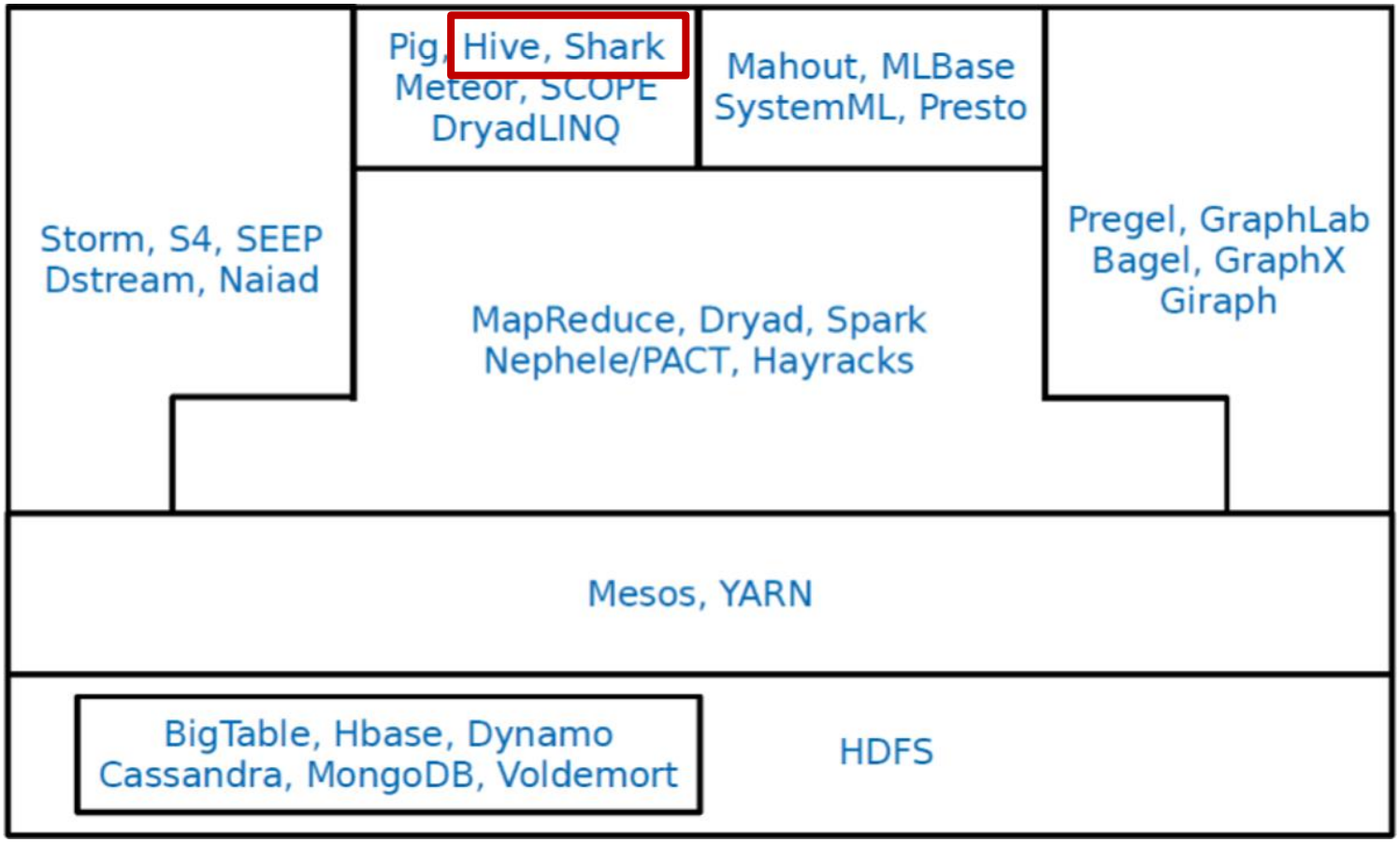


figure from: https://www.sics.se/~amir/dic.htm

Hive[Hive]

Motivation

- MapReduce programming model is low level
- Hadoop/Spark lacks expressiveness
  - end users need to write code even for simplest aggregations, hard to maintain and reuse
- Many experienced SQL developers
- Business intelligence tools already provide SQL interfaces

Hive[Hive]

- Scalable data warehouse
- Built on top of Hadoop
  - translates a query into MapReduce tasks
  - Intermediate results materialized on HDFS
- HiveQL - SQL-like declarative language + UDFs
- Data analytics at Facebook
- Open source since August 2008

DBMS applications – OLTP vs OLAP

Table: Order

order	customer
1	22
2	33

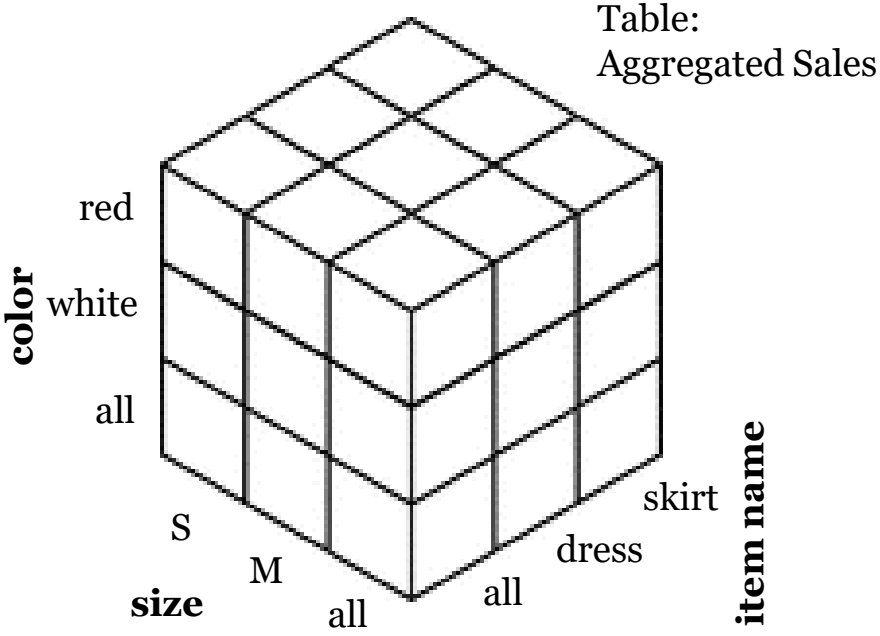
Table: Cart

order	Item	quantity
1	45	1
1	55	1
1	65	2
2	65	1

Table: Item

item	name	color	size
45	skirt	white	L
65	dress	red	M

Table: Aggregated Sales



Hive[Hive + Hadoop]

- Tables, columns, rows, partitions
  - SerDe to read/write table rows in custom format
- Types
  - Primitive & complex – maps, arrays, arbitrarily nested
  - User-defined types
- Schema-on-read *not* schema-on-write
- Updates, Locks, Indexes

Hive – Tables[Hive + Hadoop]

- The data typically is stored in HDFS
  - Tables stored in directories in HDFS

```
CREATE TABLE managed_table (dummy STRING);

LOAD DATA INPATH '/user/tom/data.txt' INTO table
managed_table;

DROP TABLE managed_table;
```

- `CREATE TABLE + LOAD DATA` ***move*** the data
- `DROP TABLE` the data and metadata are deleted, the ***data no longer exists***

Hive – External Tables[Hive + Hadoop]

- The data typically is stored in HDFS
  - External tables – when using other tools on the same dataset

```
CREATE EXTERNAL TABLE external_table (dummy STRING)
LOCATION '/user/tom/external_table';
```

- `CREATE` ***`EXTERNAL`*** `TABLE` ***does not move*** the data
- `DROP TABLE` the metadata only are deleted, the ***data continue to exist***

Hive – Partitions and Buckets[Hive + Hadoop]

- The data typically is stored in HDFS
  - Tables stored in directories in HDFS
    - Managed & external tables
  - Partitions by a partition column
    - `CREATE TABLE test_part(ds string, hr int) PARTITIONED BY (ds string, hr int)`
    - `SELECT * FROM test_part WHERE ds='2009-02-02' AND hr=11;`
  - Buckets gives extra structure; more efficient queries

Hive – Tables, Partitions and Buckets[Hive + Hadoop]

- Tables stored in directories in HDFS

  hdfs://user/hive/warehouse/table_name

- Partitions are subdirectories

  hdfs://user/hive/warehouse/table_name/partition_name

- Buckets are stored in files

  hdfs://user/hive/warehouse/table_name/bucket_name

  hdfs://user/hive/warehouse/table_name/partition_name/bucket_name

HiveQL vs SQL[Hadoop]

Feature	HiveQL	SQL
Updates	`UPDATE, INSERT, DELETE`	`UPDATE, INSERT, DELETE`
Transactions	Limited support	Supported
Indexes	Supported	Supported
Data types	SQL supported + boolean, array, map, struct	Integral, floating point, fixed point, text and binary strings, temporal
Functions	Hundreds of built-in functions	Hundreds of built-in functions
Multiple inserts	Supported	Not supported
`CREATE TABLE AS SELECT`	Supported	Not valid SQL-92, but found in some databases
`SELECT`	SQL-92. `SORT BY` for partial ordering. `LIMIT` to limit number of rows returned.	SQL-92
Joins	SQL-92 or variants (join tables in the FROM clause, join condition in the WHERE clause)	Inner joins, outer joins, semi joins, map joins, cross joins
Subqueries	In the FROM, WHERE, or HAVING clause (uncorrelated queries not supported)	In any clause. Correlated or noncorrelated.
Views	Read-only. Materialized views not supported.	Updatable. Materialized or nonmaterialized.
Extension points	User-defined functions. Map-Reduce scripts.	User-defined functions. Stored procedures.

HiveQL vs SQL[Hive]

- Change the order of the FROM and SELECT/MAP/REDUCE
- Multi inserts

```
FROM table_name
INSERT OVERWRITE TABLE table_one
SELECT table_name.column_one,table_name.column_two
INSERT OVERWRITE DIRECTORY '/output_dir'
SELECT table_name.column_two
WHERE table_name.column_one == 'something'
```

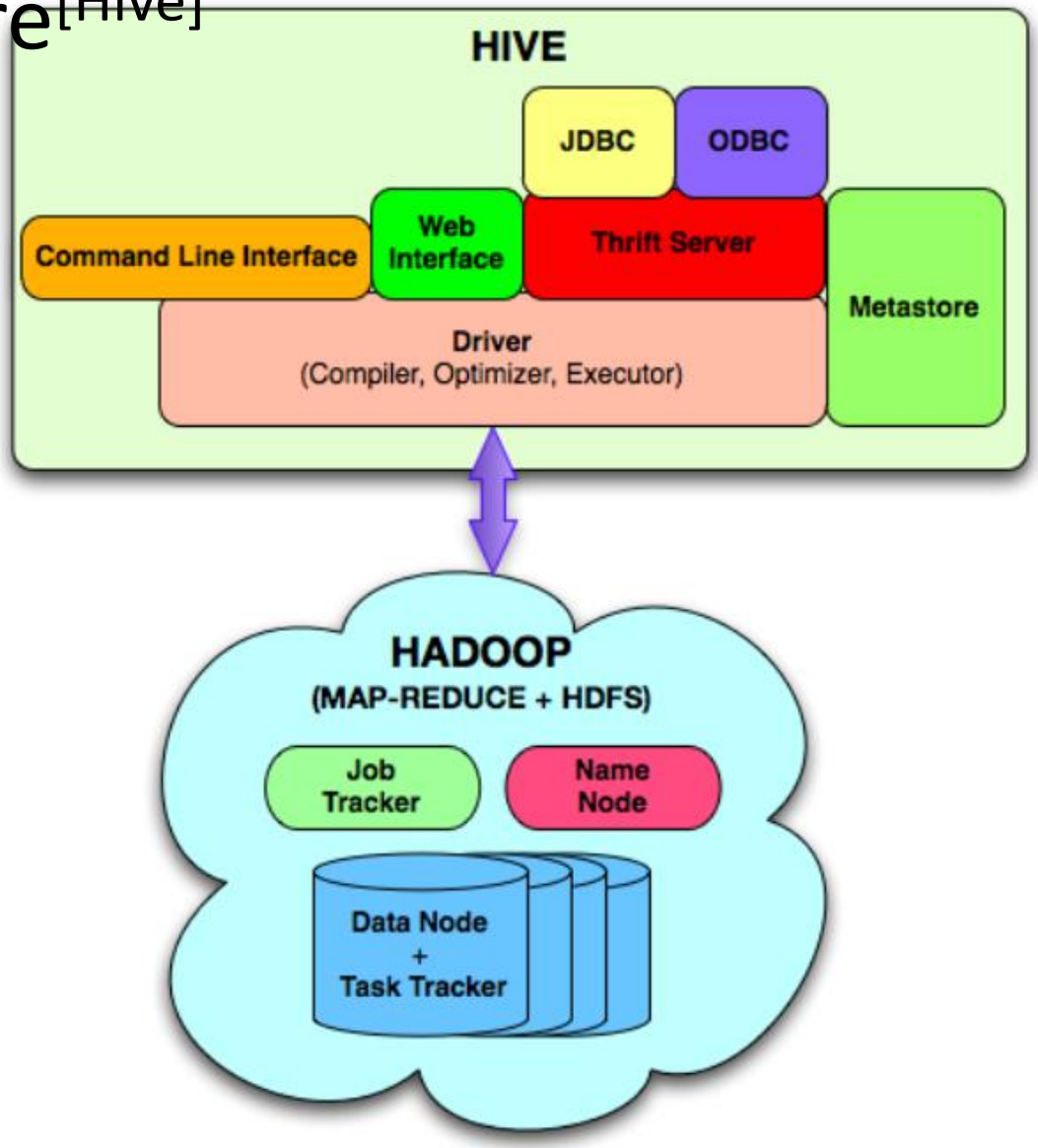
HiveQL vs SQL[Hive]

- Word Count in Hive using custom user program

```
FROM (
MAP doctext
USING 'python wc_mapper.py' AS (word, cnt)
FROM docs
CLUSTER BY word
) a
REDUCE word, cnt USING 'python wc_reduce.py';
```

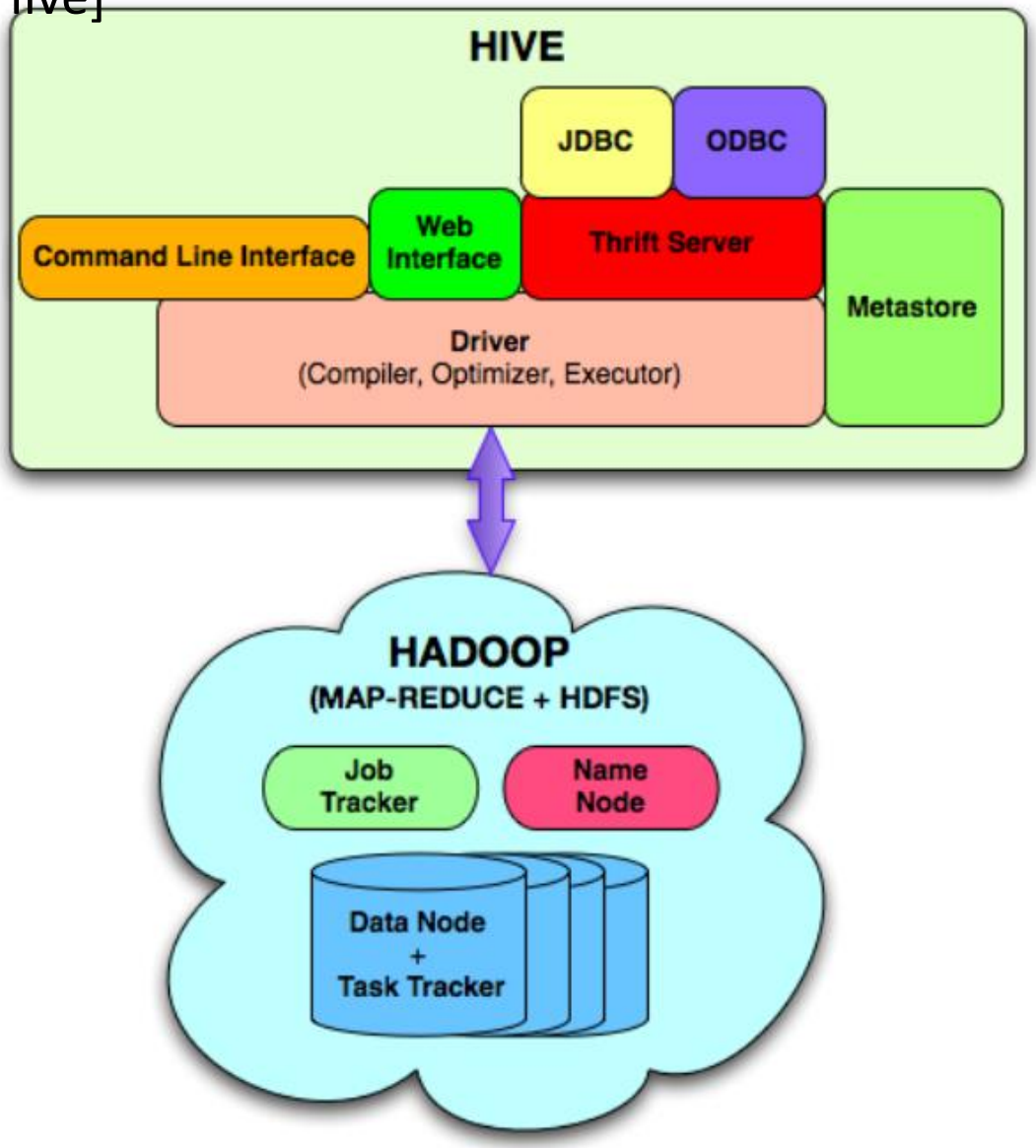
Hive – Architecture [Hive]

- Metastore
  - Served by RDBMS
  - Metadata about the tables
  - Specified at table creation time and reused when the table is referenced



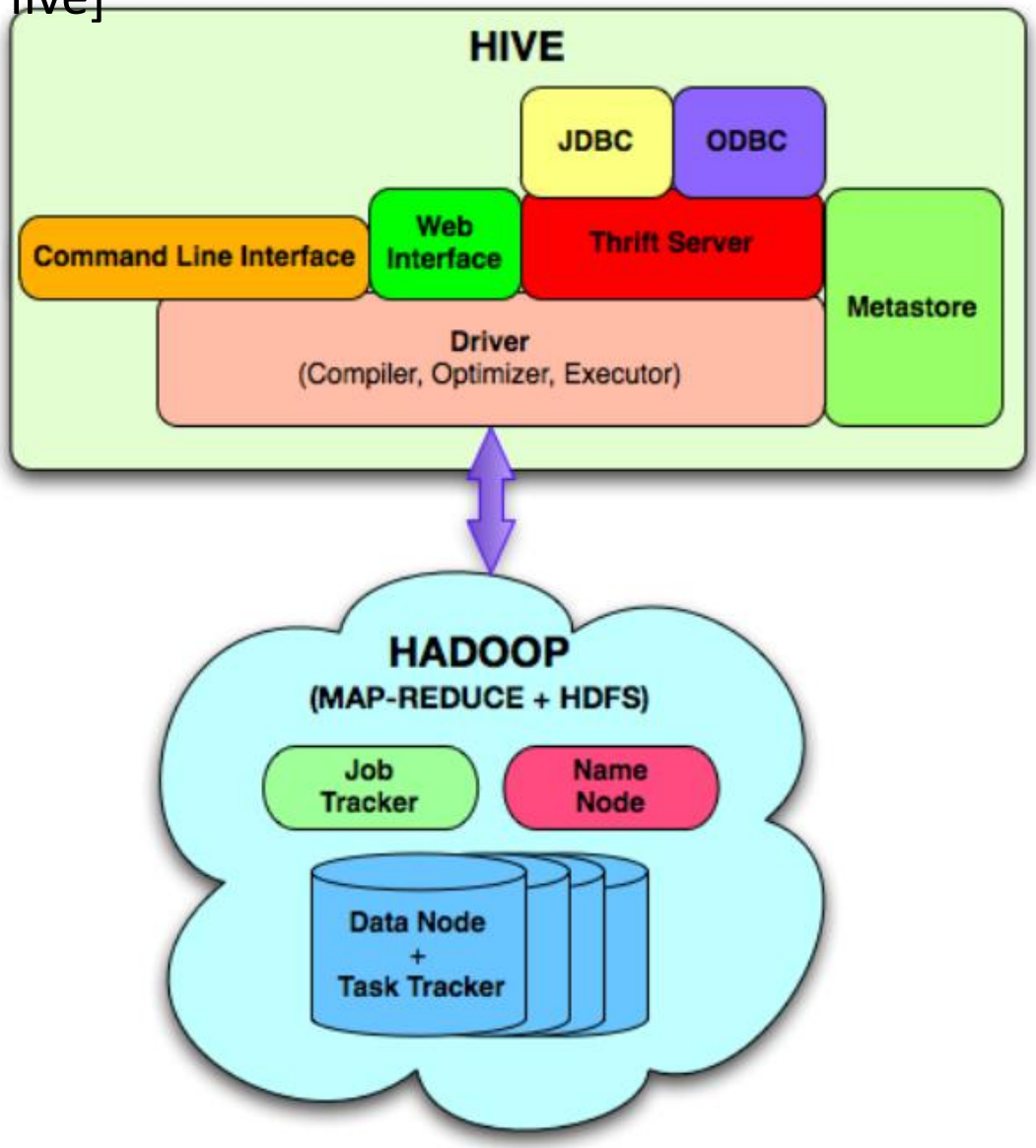
Hive – Architecture[Hive]

- Driver manages the lifecycle of a HiveQL statement:
  - Query Compiler and Optimizer – creates a logical plan from HiveQL query
  - Execution Engine - executes the plan preserving dependencies



Hive – Architecture[Hive]

- Hive server – enables access from clients written in different languages
- Hive clients
  - CLI
  - JDBC/ODBC
  - webUI



Hive - Summary

- Data warehouse translates SQL-like queries to MapReduce jobs
- HiveQL is SQL-like language with additional features
- Schema-on-read → no preprocessing
- Table partitions and buckets for more efficient queries
- Column-oriented, row-oriented and text file storage formats

SparkSQL[Shark]

Hive, Shark and SparkSQL [SparkSQLHistory]

- Hive
- Shark project started around 2011
  - built on the Hive codebase
  - swaps Hadoop with Spark
- SparkSQL
  - Shark code base hard to optimize and maintain
  - Shark and Hive compatible
    - Hive's SQL dialects, UDF (user-defined functions) & nested data types

Spark vs MapReduce

- Supports a chain of multiple transformations, not just the two-stage MapReduce topology
- Optimized for low latency
- Provides Resilient Distributed Datasets (RDDs)
  - Written in memory, much faster than the network
  - One copy & the lineage graph
  - RDDs can be rebuilt in parallel in case of failure and slow execution
    - Since RDD are immutable
  - Enables mid-query fault tolerance

Shark[Shark]

- Provides unified engine for running efficiently SQL queries and iterative machine learning algorithms
- In-memory computations
- Benefits from In-memory Resilient Distributed Datasets (RDDs) due to
  - often complex analytic functions are iterative
  - traditional SQL warehouse workloads exhibit strong temporal and spatial locality

Shark – Fault Tolerance[Shark]

- Main-memory databases
  - track fine-grained updates to tables
  - replicate writes across the network
  - expensive on large commodity clusters
- Shark
  - tracks coarse-grained operations, eg, map, join, etc.
  - recovers by tracking the lineage of each dataset and recomputing lost data
  - supports machine learning and graph computations

Shark – Fault Tolerance Properties[Shark]

- Shark can tolerate the loss of any set of worker nodes
  - Also during a query
  - Lost data will be recomputed using the lineage graph
- Lost partitions are rebuilt in parallel
- If a task is slow, it could be run on another node
- Recovery is supported for both SQL and machine learning user defined functions

Shark & Hive Architecture

- Query parsing and logical plan generation by the Hive compiler
- Physical plan generation – consists of RDDs transformations

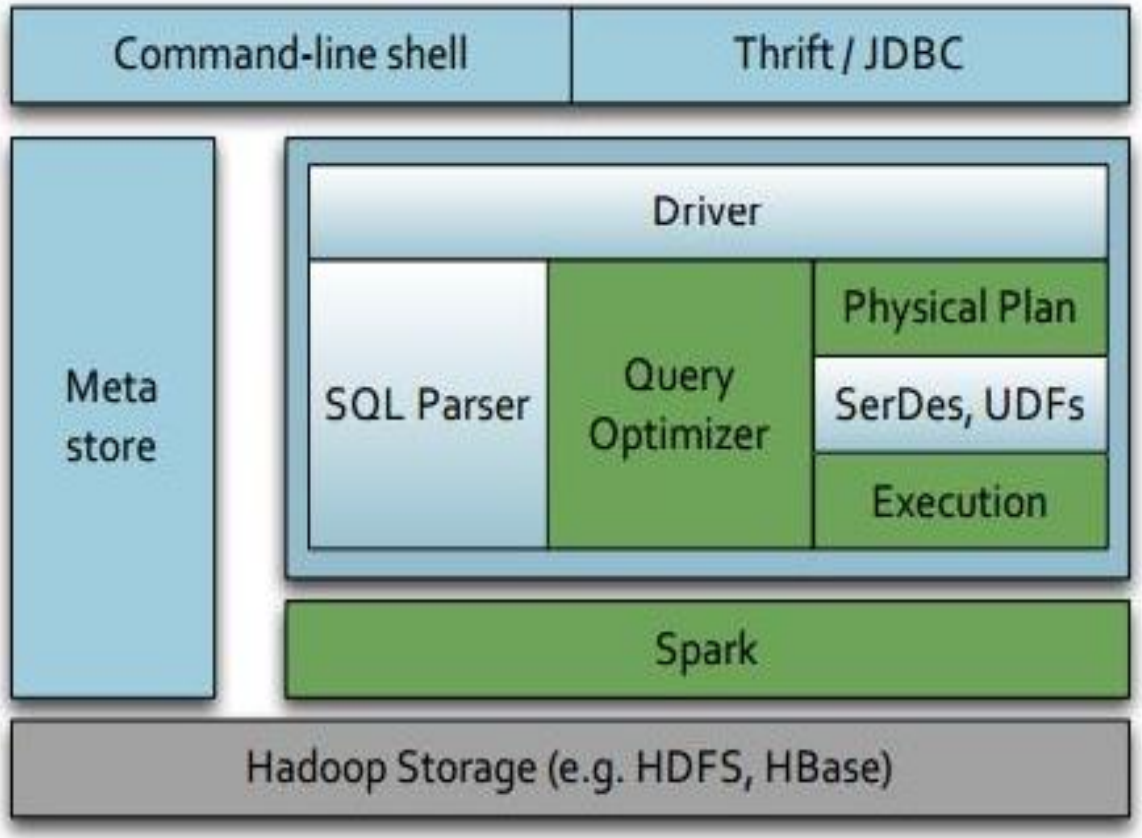


figure from http://www.rosebt.com/blog/spark-shark-and-mesos-data-analytics-stack

Shark – Query Execution[Shark]

- … but how to make it efficient given that:
  - UDF and complex analytic functions
  - Schema-on-read approach, i.e., extract-transform-load (ETL) process has been skipped thus a priory statistics for query optimization are not available

Shark Extensions

- In-memory columnar storage and columnar compression
  - Reduces data size and processing time
- Partial DAG Execution
  - Re-optimize a running query

Shark Executions[Shark]

- In-memory columnar storage – in-memory computation is essential to low-latency query answering
- Shark stores all columns of primitive types as JVM primitive arrays
  - Caching Hive records as JVM objects is inefficient → examples in the paper

Row Storage

13	1000	23
14	2000	27

Column Storage

13	14
1000	2000
23	27

Shark Extensions

- In-memory columnar storage and columnar compression
  - Reduces data size and processing time
- Partial DAG Execution
  - Re-optimize a running query

Shark Executions[Shark]

- Partial DAG Execution (PDE)
  - dynamic approach for query optimization
- The query plan is altered based on run-time collected statistics
  - Workers collect global and per partition statistics
  - Workers send them to the master
  - The master dynamically alters the query plan

Shark – Summary

- Data warehouse based on Hive
  - the latest version called SparkSQL
- Efficiently execute complex analytical queries and machine learning algorithms
- Extends Spark execution engine and uses RDDs
- Fault tolerance by tracking the lineage of the RDDs and recomputing in case of failure
  - does not rely on replication
- Tutorials: http://spark.apache.org/docs/latest/sql-programming-guide.html

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