Aalto University
School of Science

Hadoop and its Big Data Ecosystems

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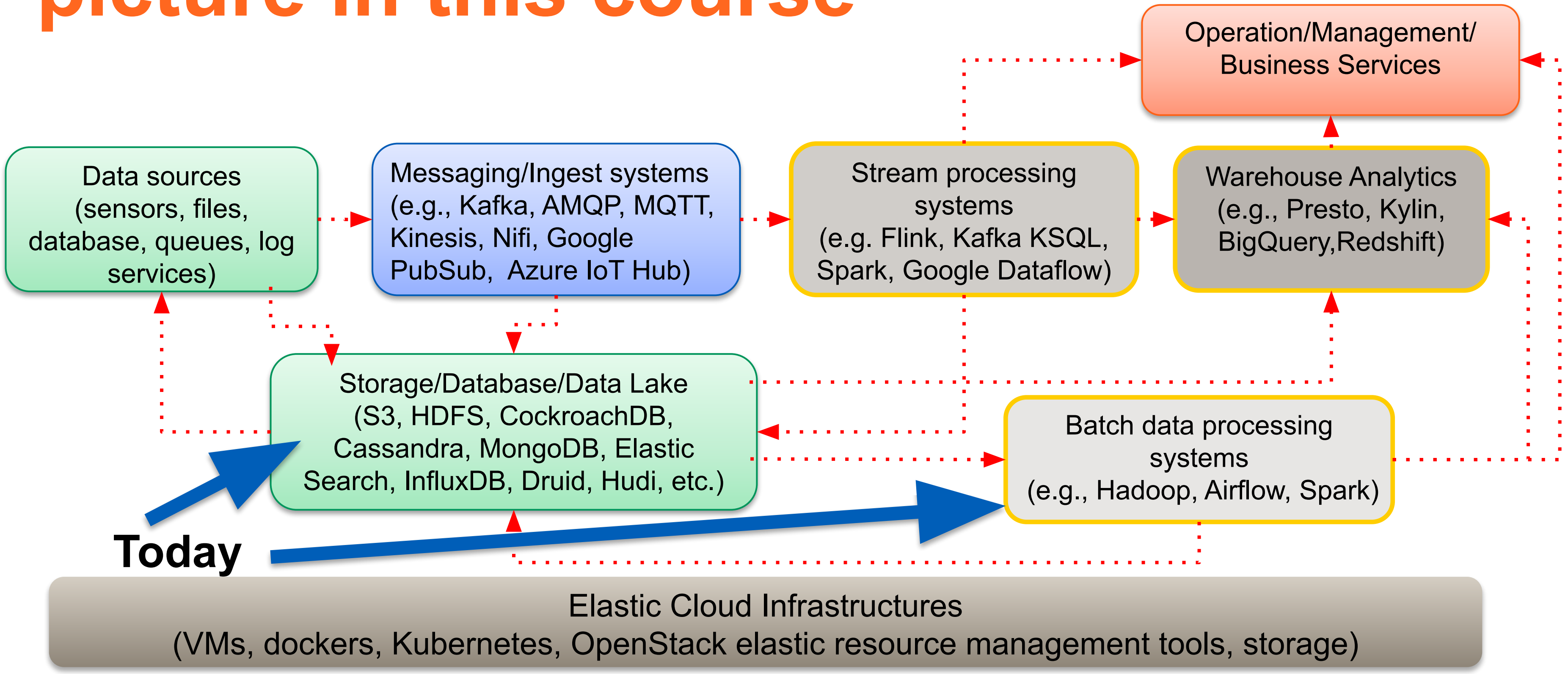
Learning objectives

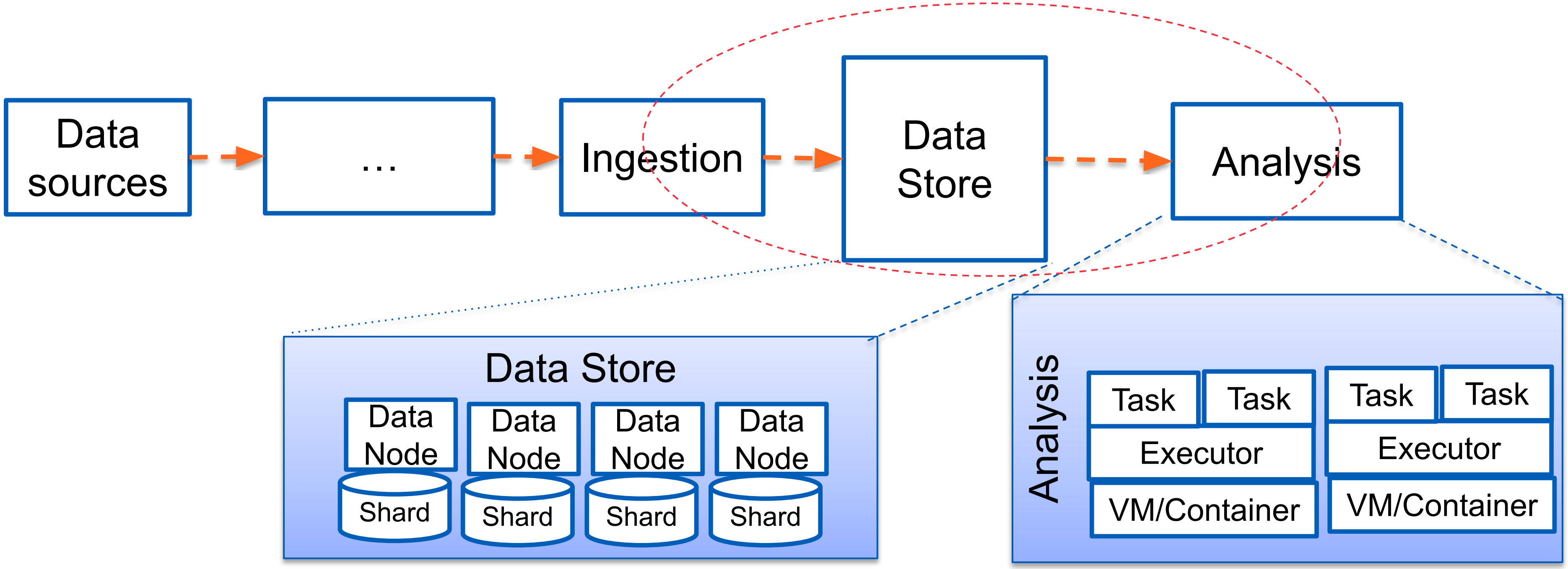
- Understand massive scale data management and processing with Hadoop
- Understand and able to use Hadoop components for big data platform designs
- Able to integrate Hadoop with other frameworks for data ingestion and analytics systems

Big data at large-scale: the big picture in this course



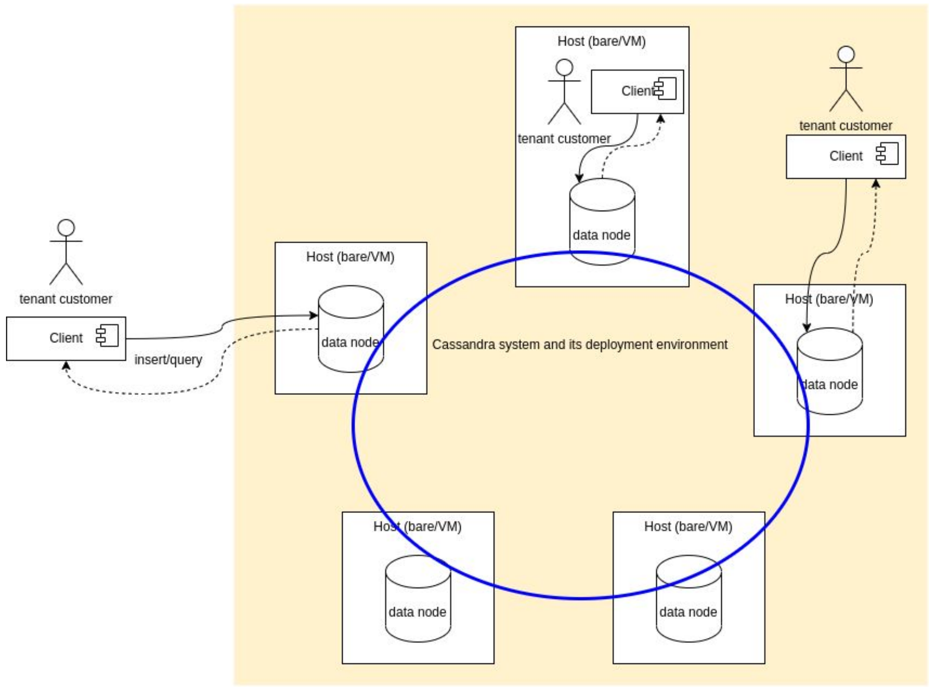
Operation/Management/ Business Services
Data sources (sensors, files, database, queues, log services)
Messaging/Ingest systems (e.g., Kafka, AMQP, MQTT, Kinesis, Nifi, Google PubSub, Azure IoT Hub)
Stream processing systems (e.g. Flink, Kafka KSQL, Spark, Google Dataflow)
Warehouse Analytics (e.g., Presto, Kylin, BigQuery,Redshift)
Storage/Database/Data Lake (S3, HDFS, CockroachDB, Cassandra, MongoDB, Elastic Search, InfluxDB, Druid, Hudi, etc.)
Batch data processing systems (e.g., Hadoop, Airflow, Spark)
Today
Elastic Cloud Infrastructures (VMs, dockers, Kubernetes, OpenStack elastic resource management tools, storage)

Consider again our big data pipelines



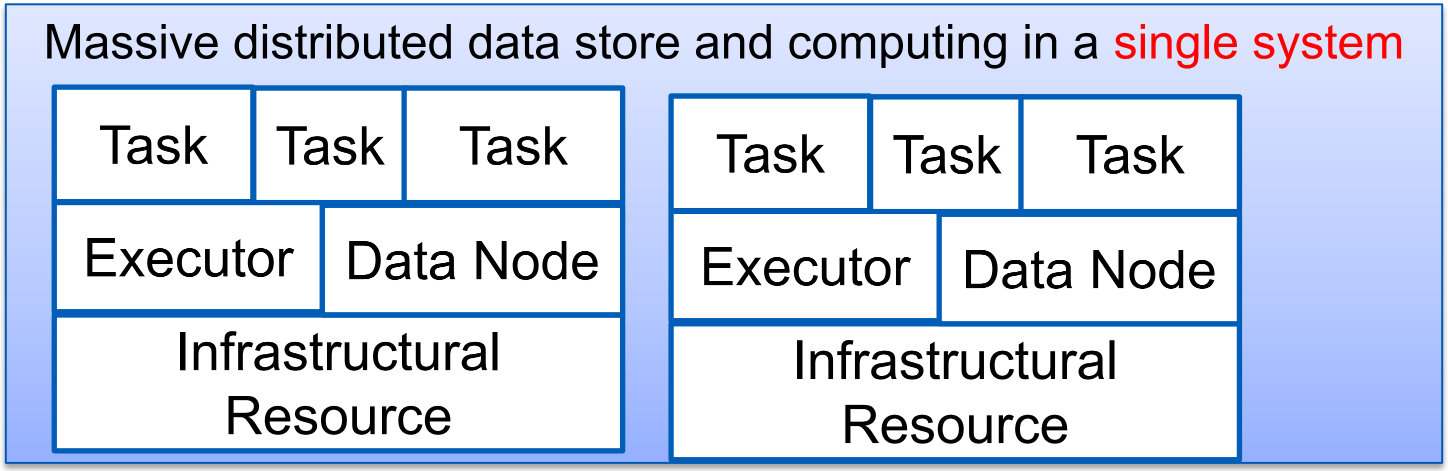
Except ingestion/queries, most analytics are done outside the data system

Data store: E.g., Cassandra



Combining data storage and analysis

Data locality, massive parallel and distributed data processing with large-scale data store

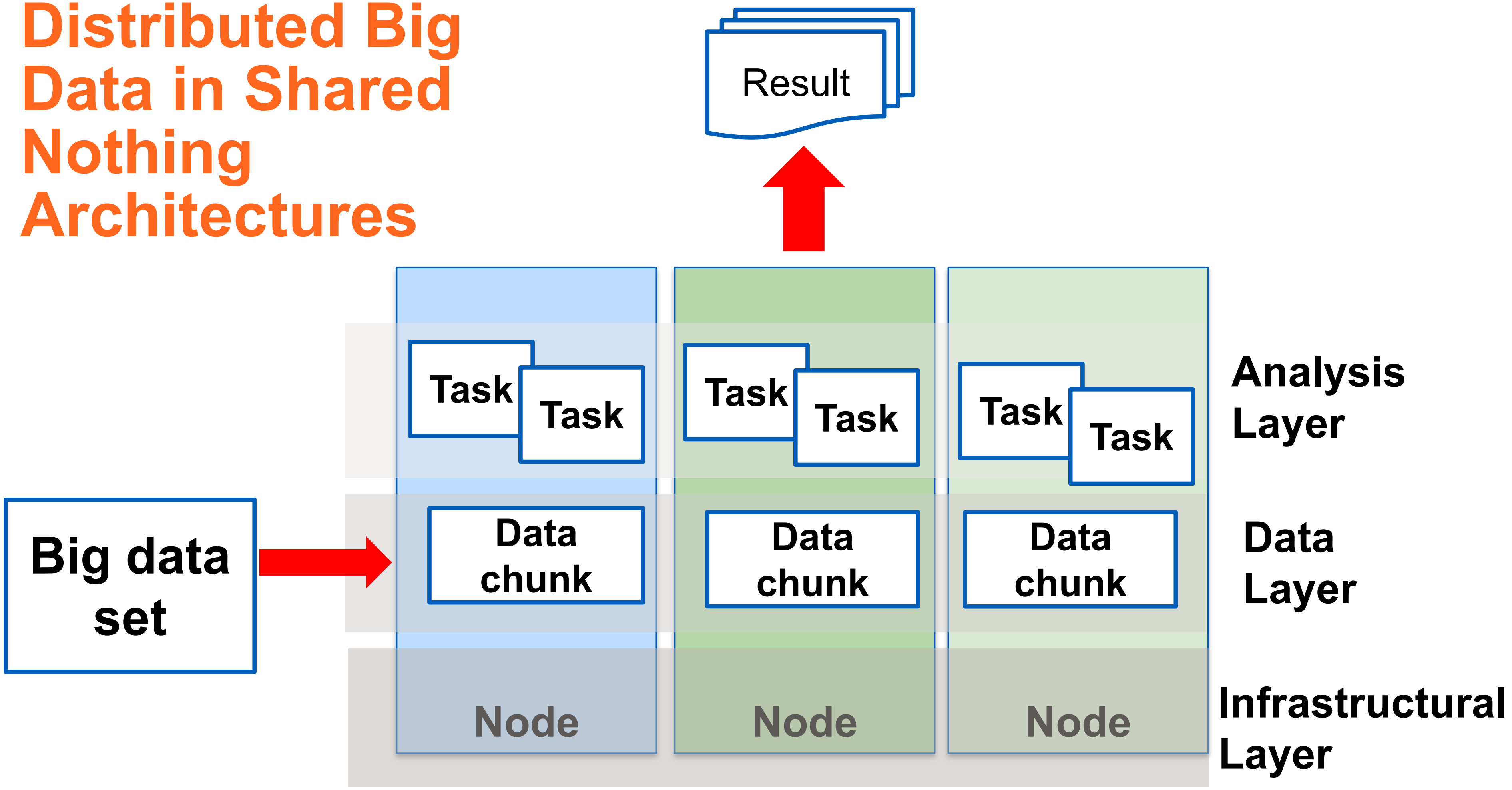


Single system: many machines connected into a type of "cluster"

Shared nothing architectures

- **Machine as a node:**
  - completely independent from other nodes
  - no shared physical resources (CPUs, memory, hard disk, ...)
- **A distributed system of machines with shared nothing architectures**
  - allow to scale and extend physical resources easily
  - enable high fault tolerance designs
  - quite common and easy-to-be-setup for enterprises
    - *think about commodity clusters*

Distributed Big Data in Shared Nothing Architectures



Benefit

- Reduce cost and increase performance when moving data is much more expensive than moving computation
- Consolidate and integrate various types of data
- Save shared infrastructural resources
- Provide suitable solutions for different types of customers/clients and different infrastructures

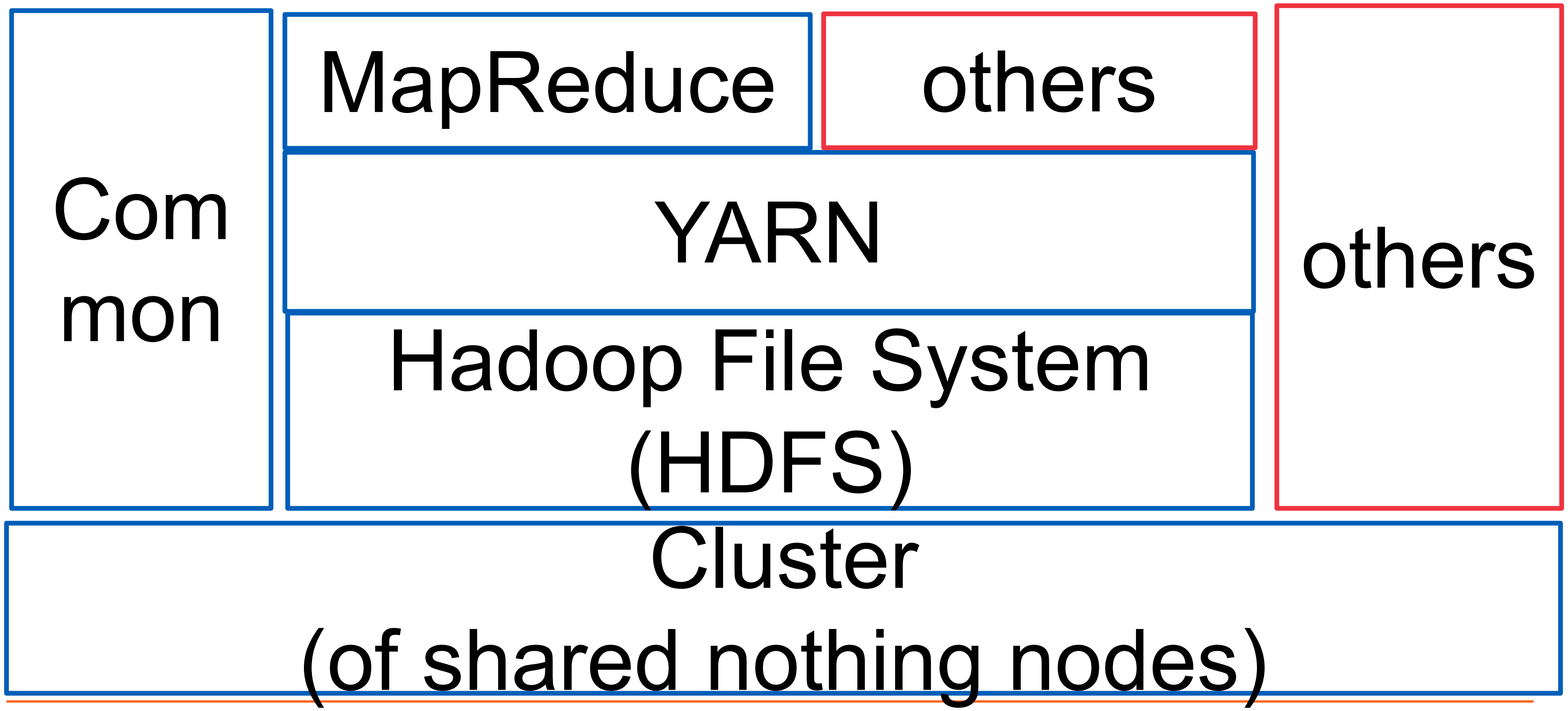
Benefit - Variety

- **Multiple data formats in files**
  - direct access by applications or low-level storage layer
- **In big data we have a lot of files**
  - do not need to transform them into a single format or database
  - file storage as the data lake storage layer
- **Processing files directly is a benefit!**
- **The data lake concept:**
  - multiple types of big data analytics with high concurrent/parallel data writes/reads
  - dealing with different data access frequencies: **hot, warm and cold data**

Hadoop

- http://hadoop.apache.org/, original from Yahoo
- The goal is to combine storage and processing in the same cluster system
- Designed for ***massive scale of data and computing with shared nothing architecture***
    - commodity hardware, highly scalability, fault tolerance, easy to extend
- Suitable for both on-premise and clouds
- There are very rich software ecosystems centered around Hadoop

Hadoop: layers



Hadoop key components

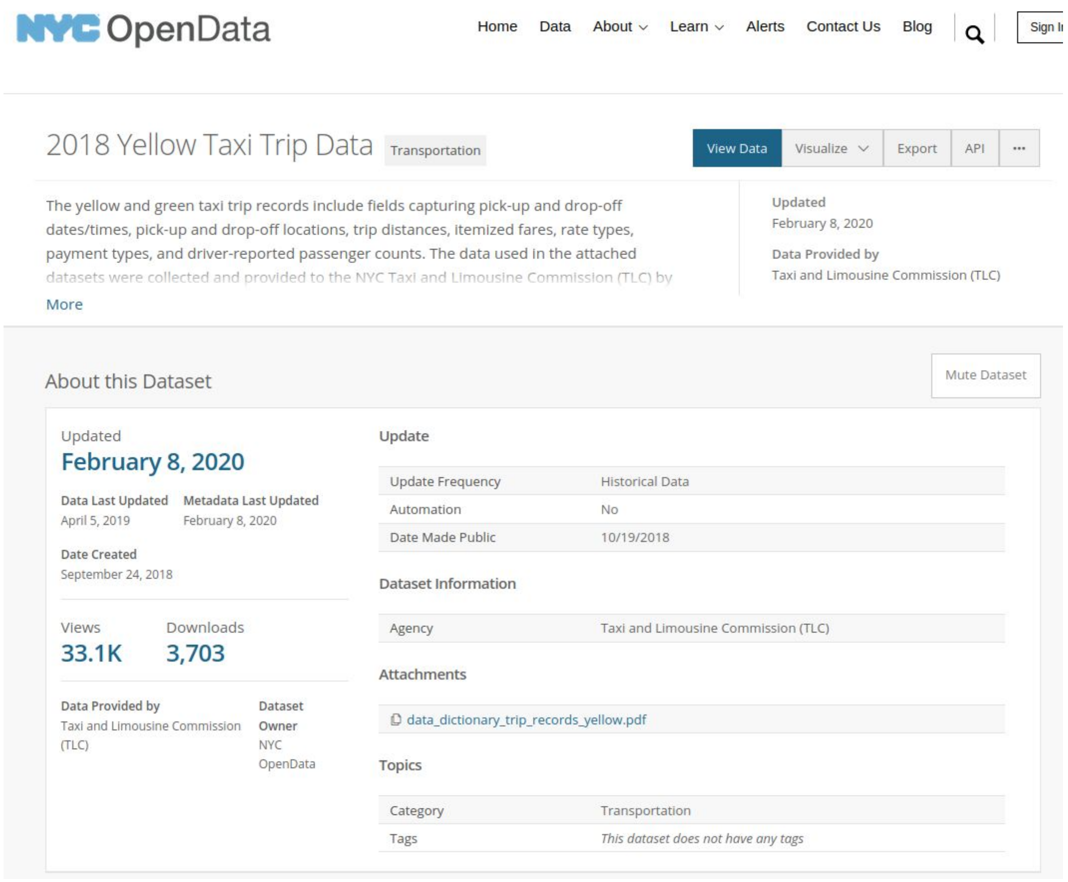
- **HDFS as a distributed file system**
  - for managing data
- **YARN as a resource management system**
  - for executing and managing analytics tasks
- **MapReduce as one programming model**
  - for MapReduce applications
- **Coordination (ZooKeeper)**
  - for fault tolerance and metadata

Hadoop File System (HDFS)

- **For handling very big data files**
  - GBs of data within a single file
- **Assumption of data handling**
  - write-once-read-many
  - not suitable for random-access update → analytics data
- **Deal with hardware failures, support data locality, reliability**
  - “high fault tolerance” with “low-cost/commodity hardware”

Example

e.g., 112M rows



2018 Yellow Taxi Trip Data Transportation

The yellow and green taxi trip records include fields capturing pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts. The data used in the attached datasets were collected and provided to the NYC Taxi and Limousine Commission (TLC) by

More

Updated
February 8, 2020

Data Provided by
Taxi and Limousine Commission (TLC)

About this Dataset

Updated
February 8, 2020

Data Last Updated
April 5, 2019

Metadata Last Updated
February 8, 2020

Date Created
September 24, 2018

Views
33.1K

Downloads
3,703

Data Provided by
Taxi and Limousine Commission (TLC)

Dataset Owner
NYC OpenData

Update

Update Frequency	Historical Data
Automation	No
Date Made Public	10/19/2018

Dataset Information

Agency	Taxi and Limousine Commission (TLC)

Attachments

data_dictionary_trip_records_yellow.pdf

Topics

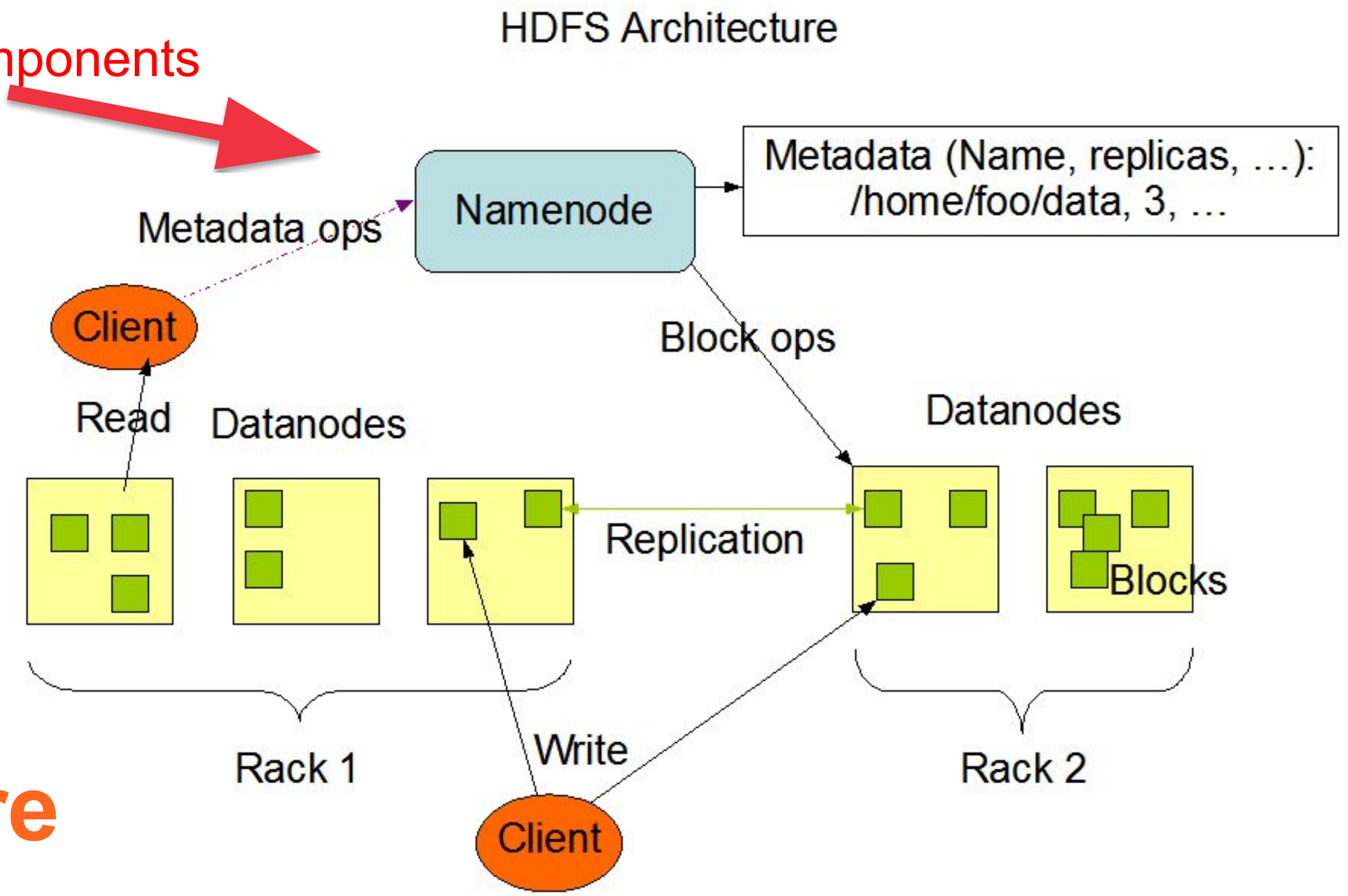
Category	Transportation
Tags	*This dataset does not have any tags*

Snapshot from: https://data.cityofnewyork.us/Transportation/2018-Yellow-Taxi-Trip-Data/t29m-gskq

HDFS - data blocks

- **Files are stored in many nodes**
  - but the application accesses HDFS files just like “typical file systems”
- **A file includes many blocks**
- **File blocks are replicated and distributed across nodes**
- **Conventional way of access data**
  - naming resolving: hdfs://
  - common operations: list, put, get, …

Crucial components



HDFS Architecture

Figure source: https://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html

File blocks, metadata and data replication

- **Block size is 128MB (default)**
  - can be configurable but should not be small size
  - all blocks of the same file are the same, except the last one
- **Data is replicated across the cluster**
  - usually, replication factor is 3
- **NameNode manages file system metadata**

HDFS fault tolerance

- **Data blocks**
  - file blocks are replicated and distributed across nodes
- **Rack awareness**
  - avoid communication problems between nodes in different racks
- **Monitoring**
  - DataNode reports to NameNode
- **Read and write**
  - using NameNode for metadata and for information of DataNodes
  - NameNode has replication (master-worker)

Compatible file systems with HDFS

- **Many file systems are compatible with HDFS**
  - for integration and analysis purpose: m
- **Examples:**
  - Amazon S3
  - Azure Blob Storage
  - Azure Data Lake Storage
  - OpenStack Swift

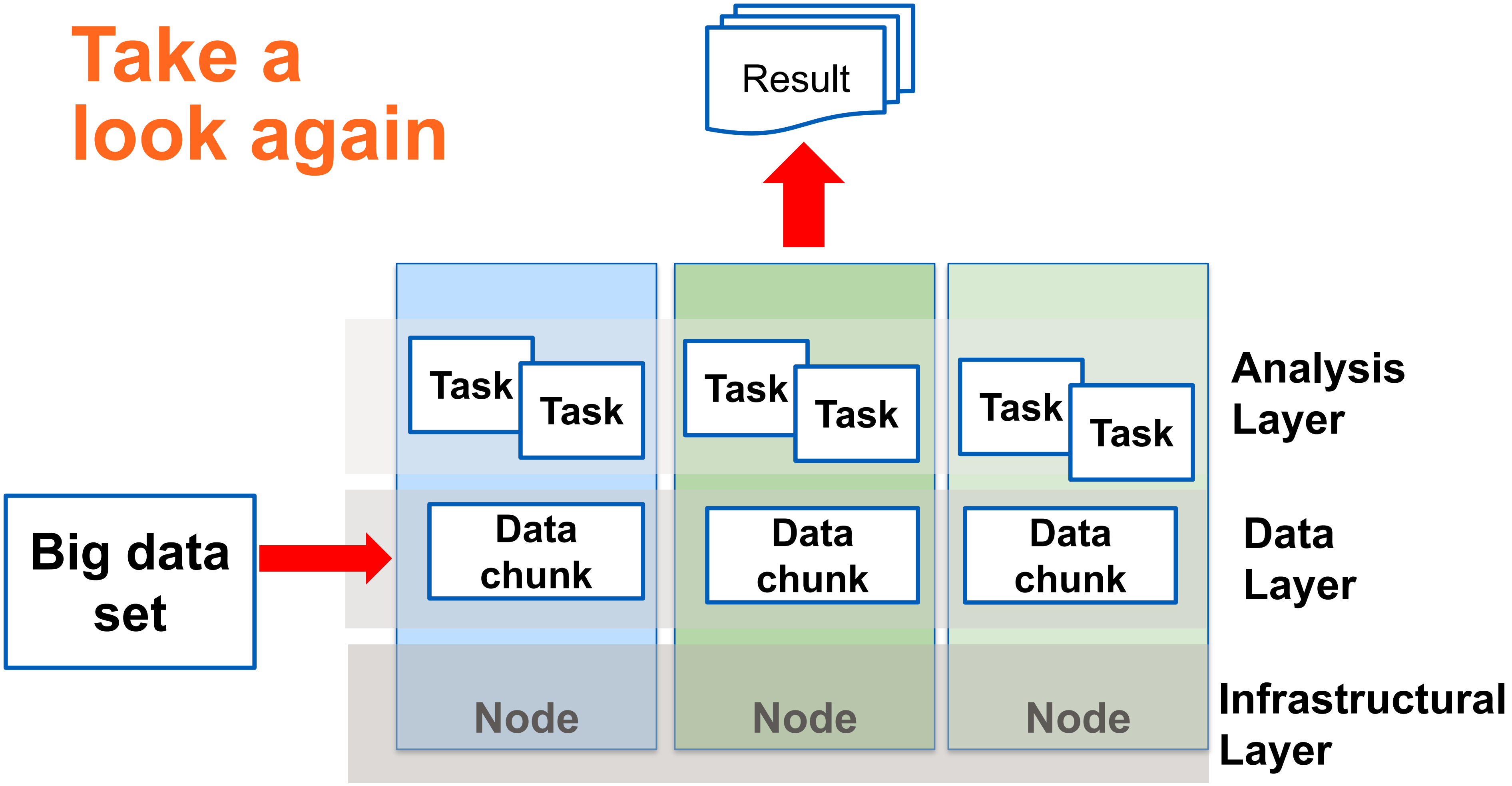
YARN (Yet Another Resource Negotiator)

If HDFS can be used to store different files, what would be the good way to enable "data processing" atop HDFS?

Key requirements:

scalability/elasticity, high utilization of infrastructural resources, serviceability for multiple users/application types

Take a look again



How to leverage the same infrastructure and data management layers to perform data analysis?

How to enable different (distributed) programming models for data analytics?

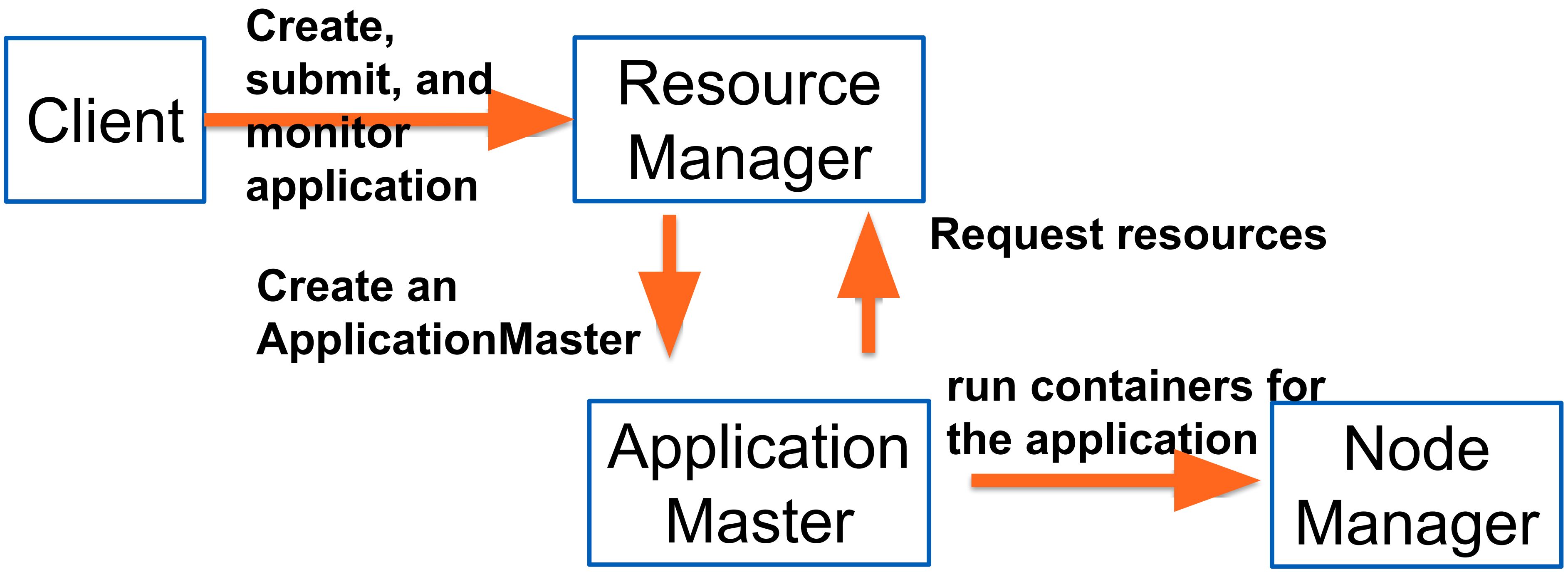
YARN (Yet Another Resource Negotiator)

- **Manage resources for processing tasks**
  - each node in the cluster provides resources for executing tasks
- **Computing resource types:**
  - CPU, Memory and Disks
  - also support GPU and FPGA Node
- **Computing resources are abstracted into "Containers"**
  - don't be confused: it is not a (Docker) container!
- **Multi-tenancy support**

YARN Components

- **Resource Manager**
  - scheduler: how to schedule analytics tasks atop computing resources
- **NodeManager**
  - for managing resources of execution tasks in a node
- **ApplicationMaster**
  - application-specific manager for each application
  - work with Resource Manager and NodeManager provisioning resources and manage application execution
  - handle application-specific tasks

YARN basic model


Client
Create, submit, and monitor application
Resource Manager
Create an ApplicationMaster
Request resources
Application Master
run containers for the application
Node Manager

YARN Architecture

User applications running within "Containers":

This model decouples from specific types of applications

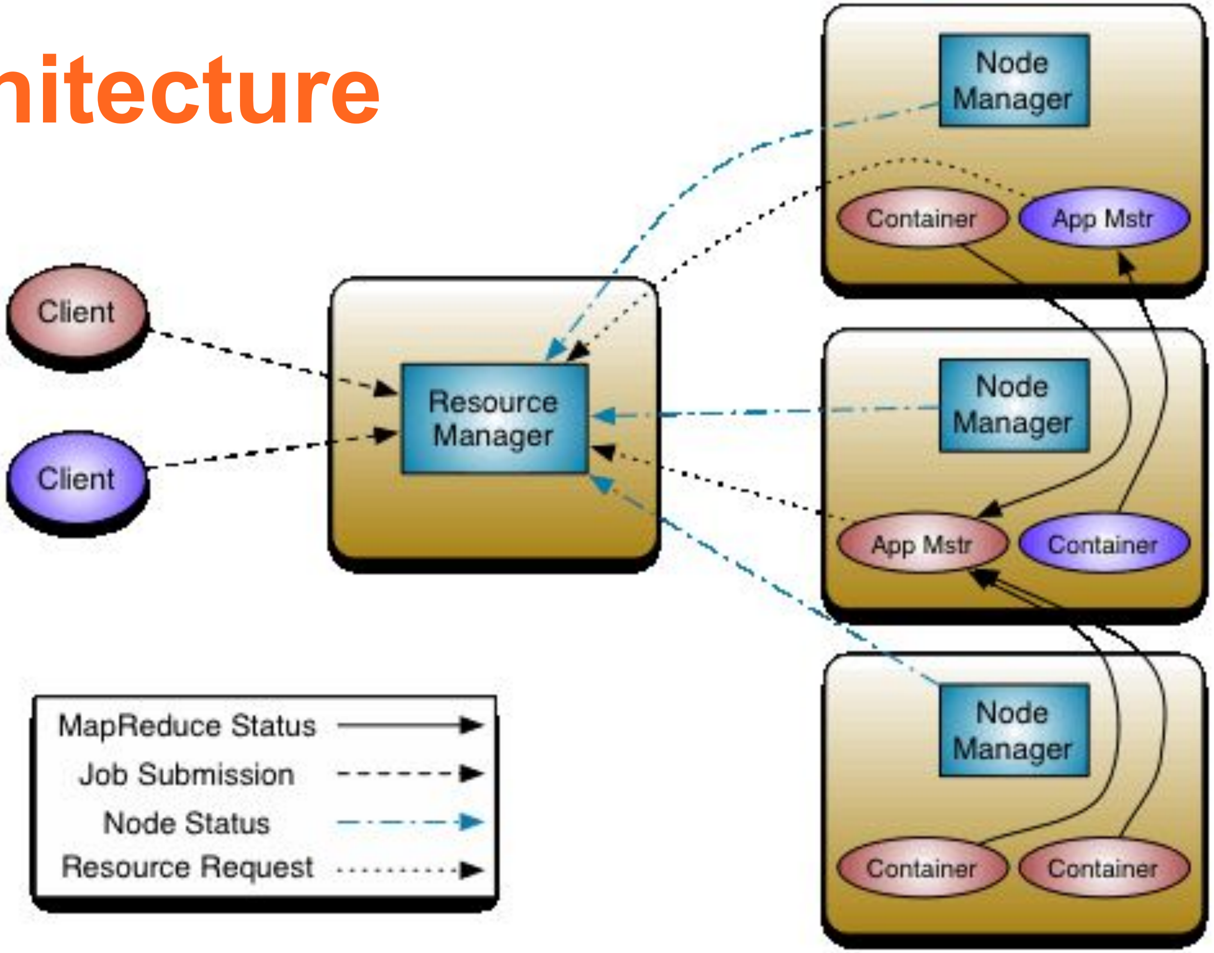


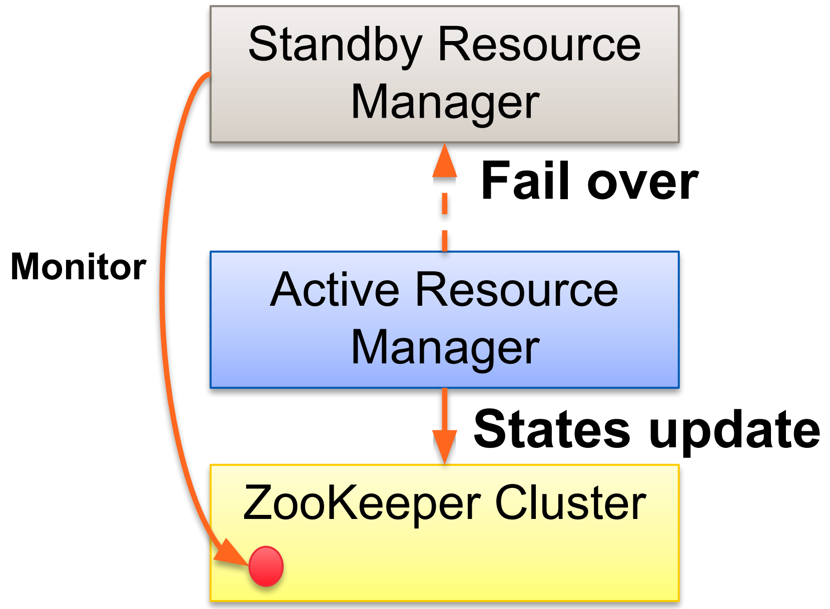
Figure source: https://hadoop.apache.org/docs/stable/hadoop-yarn/hadoop-yarn-site/YARN.html

Scheduling of tasks

- **Scheduling**
  - FIFO
  - CapacityScheduler
    - *Use multiple queues, each with a limit of resources*
  - FairScheduler
    - *All apps will get an average share of resources over time*
- **You can research and add new types of scheduling algorithms**

Fault tolerance

- **Resource Manager is a critical component**
    - active-passive Resource Manager
    - Zookeeper quorum failover
- **ApplicationMaster**
    - ApplicationMaster is application-specific
    - Resource Manager restarts AM
- **Node**
    - remove out of the cluster



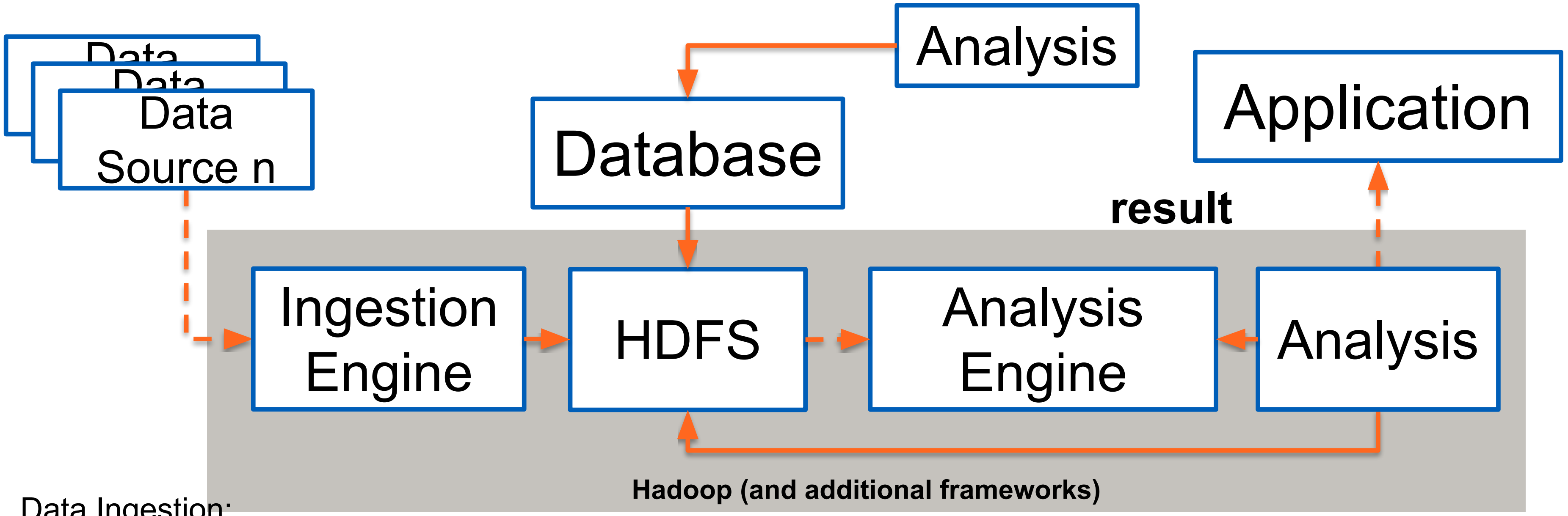
Programming models

- **YARN is an execution environment**
- **YARN allows different programming models for applications**
    - MapReduce
    - Apache Spark
    - Workflows
        - *E.g., Apache Tez for DAG (direct acyclic graph) of data processing tasks*

Integration models

- **Using Hadoop for developing large-scale data analysis**
  - Apache Spark, HBase, Hive, Apache Tez
- **Using Hadoop HDFS as components in a big data system**
  - Hadoop HDFS can become data storage → storage layer
  - emerging data lake models, combined batch and stream ingestions for incremental data processing
    - *e.g., Apache Hudi*

ETL and Analytics with Hadoop/HDFS

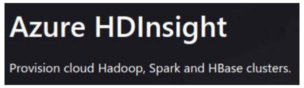


- Data Ingestion:
  - HDFS Client/Hadoop Streaming
  - Spark Streaming
  - Kafka Connect
  - Apache Nifi
- HDFS as storage for databases
  - Accumulo, Druid, etc.
- Computing/Data Processing Framework
  - Apache Spark
  - Hadoop MapReduce
  - Apache Tez

Is that Hadoop dead/unattractive?

- **Hadoop is for shared nothing architecture**
- **Shared nothing architectures are not "modern"?**
  - new, advanced developments w.r.t. memory, networks, ...
  - in-memory processing, move data to computing nodes
- **Many tools seem not powerful for data science/ML?**
  - Java vs Python development for data science and ML
  - services in ecosystem
  - near realtime analytics use cases
- **So why do we still study it?**
  - foundational designs & still many Hadoop services are important (data warehouse, deep storage)
  - well-supported by many cloud providers for big data workloads

e.g.,


Azure HDInsight

Provision cloud Hadoop, Spark and HBase clusters.

Products / Analytics / Amazon EMR

Apache Hadoop on Amazon EMR

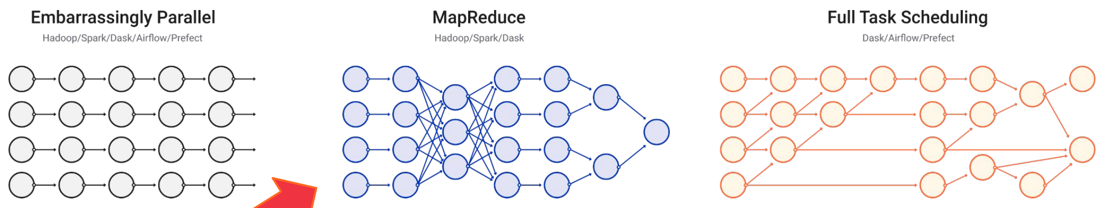
Dataproc

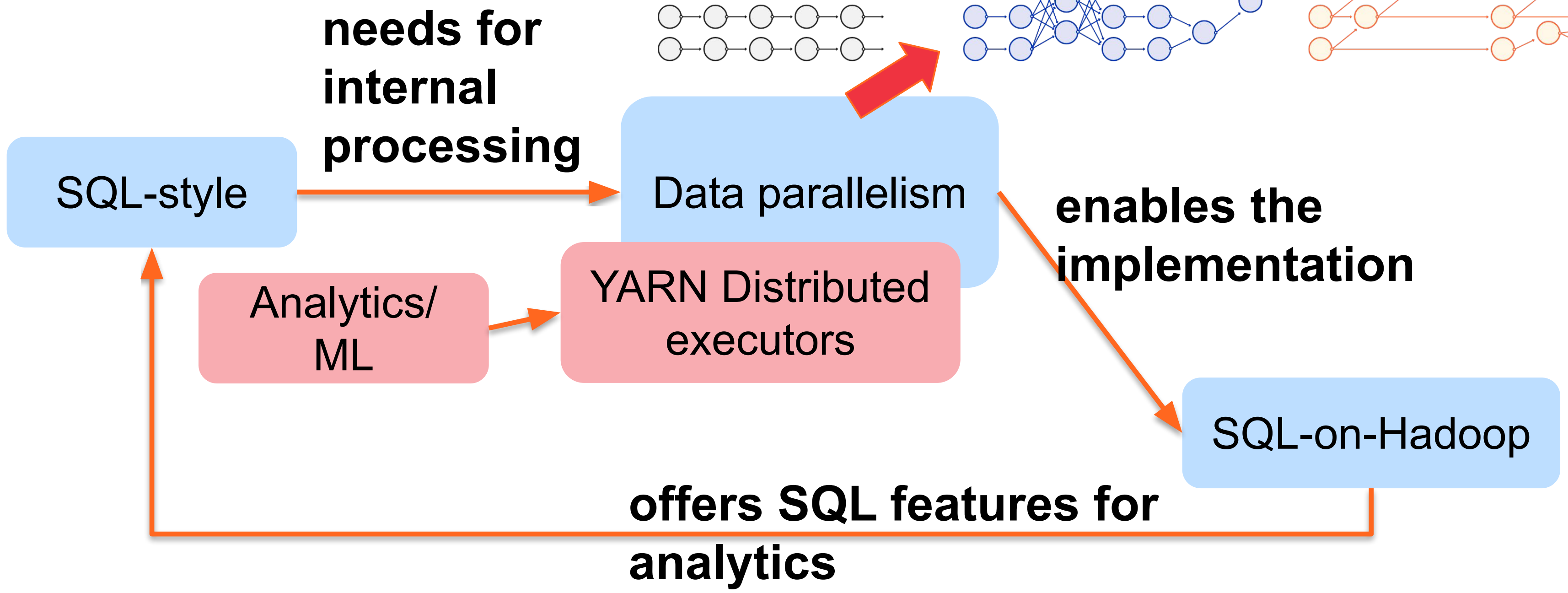
Why do we still need to learn Hadoop?

- **Hadoop file systems as a storage for many big data services**
  - databases: Accumulo, Apache Druid
  - data warehouses/Data Lakes: Hive, Hudi
- **Support different models of access/analytics**
  - via SQL styles atop big data platforms: You can do extract/transform/load (ETL), reporting, and data analysis using SQL styles
  - large-scale parallel programming (e.g., Spark)
- **Still many needs, given shared nothing architectures and on-premise conditions**

Why do we still need to learn Hadoop?

Figure source: https://docs.dask.org/en/stable/graphs.html

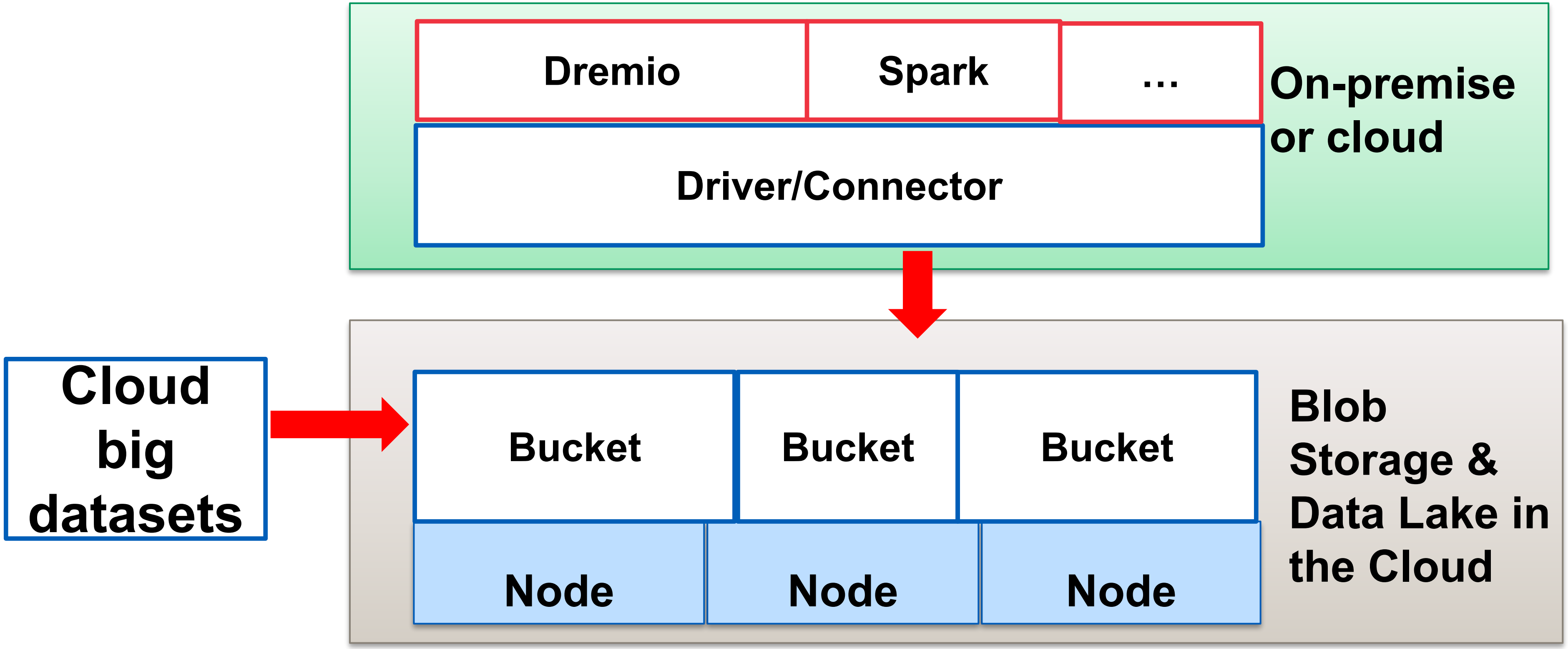



SQL-style
needs for internal processing
Data parallelism
enables the implementation
SQL-on-Hadoop
offers SQL features for analytics
Analytics/ ML
YARN Distributed executors

Enabling analysis big data using SQL style

- **Provide command line tools & JDBC and server for integration**
- **"SQL-on-Hadoop"**
- **Examples**
  - Apache Hive, https://hive.apache.org/
    - *Data warehouse, access data in HDFS or Hbase*
  - Apache Druid (using HDFS as a deep storage)
  - Spark SQL for various types of files

Integration with other cloud storage services



Hadoop-native big database/data warehouse systems

HBase

- **NoSQL database atop Hadoop**
  - use HDFS for storing data
  - use YARN for running jobs on data
- **Follow a master-based architecture**

Reading – Why HBase?
https://engineering.fb.com/2010/11/15/core-data/the-underlying-technology-of-messages/
https://engineering.fb.com/2014/06/05/core-data/hydrabase-the-evolution-of-hbase-facebook/
https://engineering.fb.com/2018/06/26/core-data/migrating-messenger-storage-to-optimize-performance/

Recall: Big data: column-family data model

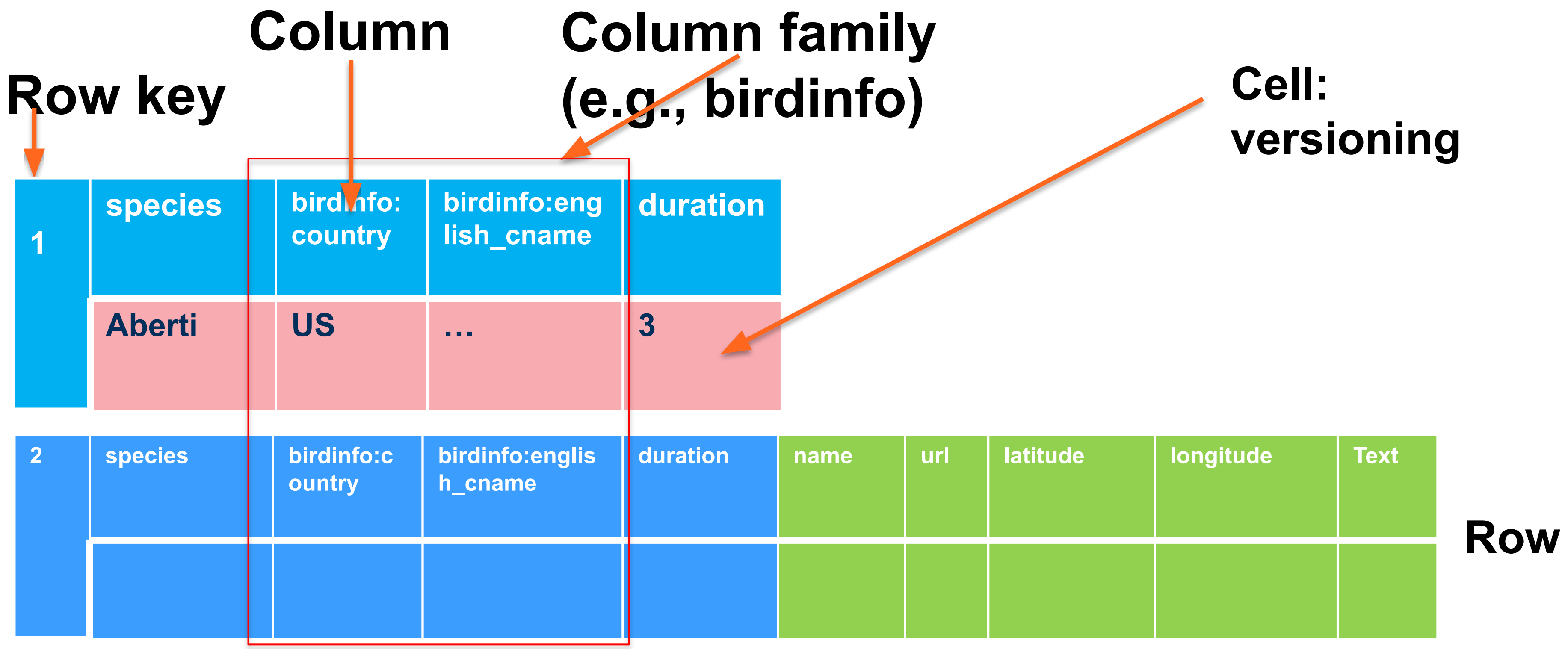
Many situations we aggregate and scan few columns of million rows of data ⇒ store big data in columns enable fast scan/retrieval/aggregation

Column Family = (Column, Column, …): **for similar type of data & access patterns**

Column Key =Family: qualifier

Data = (Key, Value) **where Key =(Row Key, Column Key, Timestamp)**

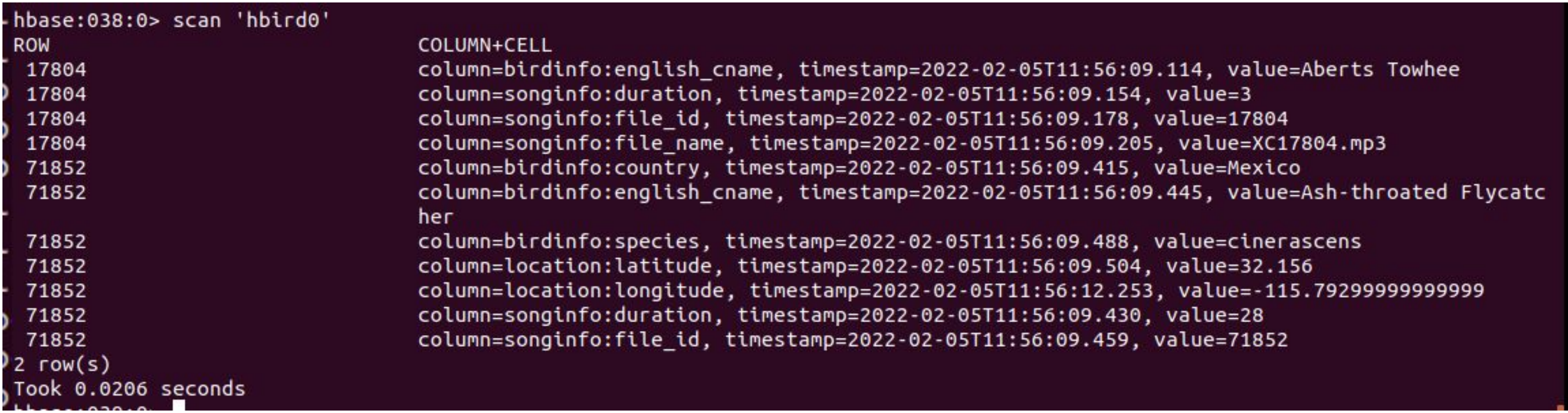
Example of a data model in HBase



Sparsely stored: not all rows have the same number of columns

Example of a data model

- **Example with families: birdinfo, songinfo, location**



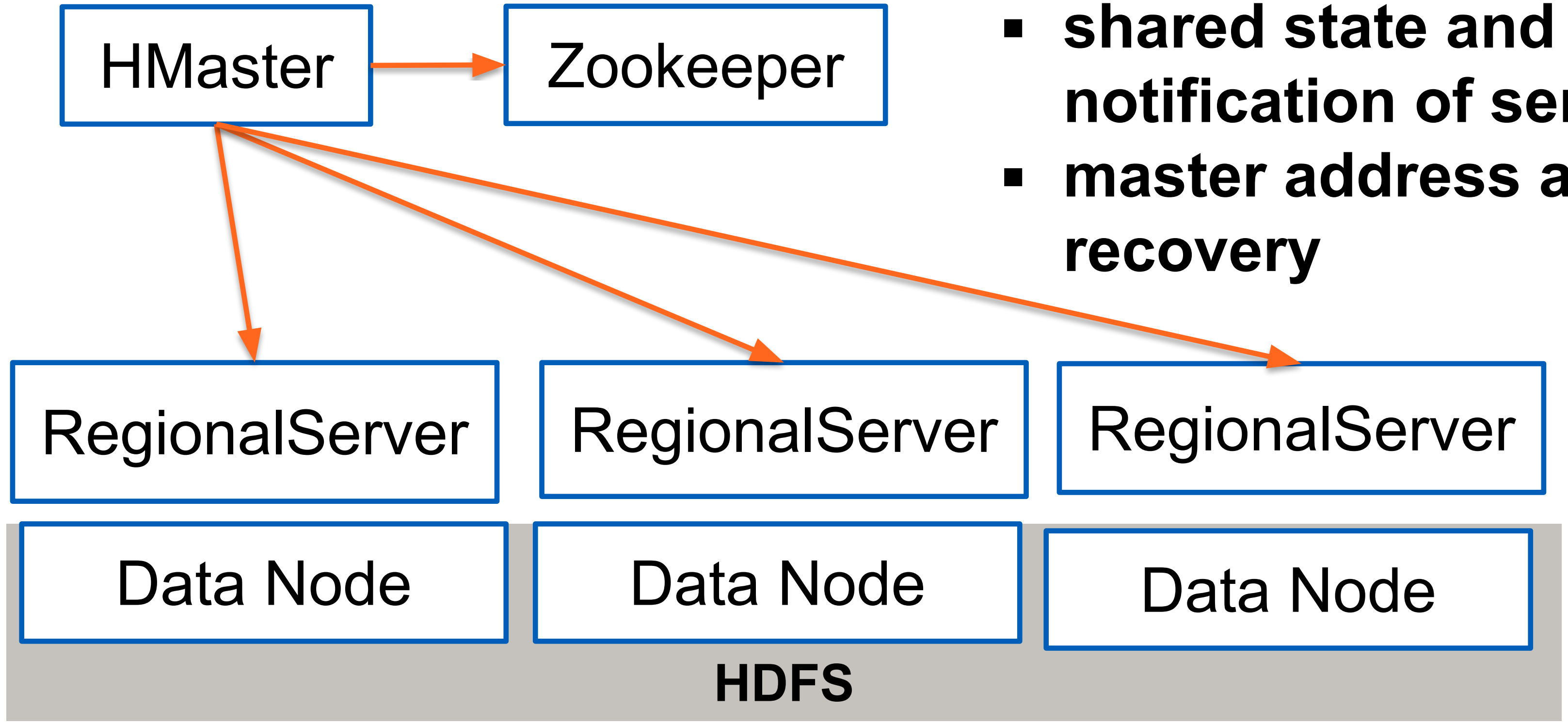
```
hbase:038:0> scan 'hbird0'
ROW                              COLUMN+CELL
 17804                           column=birdinfo:english_cname, timestamp=2022-02-05T11:56:09.114, value=Aberts Towhee
 17804                           column=songinfo:duration, timestamp=2022-02-05T11:56:09.154, value=3
 17804                           column=songinfo:file_id, timestamp=2022-02-05T11:56:09.178, value=17804
 17804                           column=songinfo:file_name, timestamp=2022-02-05T11:56:09.205, value=XC17804.mp3
 71852                           column=birdinfo:country, timestamp=2022-02-05T11:56:09.415, value=Mexico
 71852                           column=birdinfo:english_cname, timestamp=2022-02-05T11:56:09.445, value=Ash-throated Flycatc
                                 her
 71852                           column=birdinfo:species, timestamp=2022-02-05T11:56:09.488, value=cinerascens
 71852                           column=location:latitude, timestamp=2022-02-05T11:56:09.504, value=32.156
 71852                           column=location:longitude, timestamp=2022-02-05T11:56:12.253, value=-115.79299999999999
 71852                           column=songinfo:duration, timestamp=2022-02-05T11:56:09.430, value=28
 71852                           column=songinfo:file_id, timestamp=2022-02-05T11:56:09.459, value=71852
2 row(s)
Took 0.0206 seconds
```

Enable analytics based on column families (as well as data management)

HBase data model – sharding and storage

- **Table includes multiple Regions**
  - a Region keeps related row data of a Table (*partitioning*)
- **Auto-sharding**
  - Regions are spitted based on policies
- **Region has data of multiple column families**
  - Different column families will be stored in different files
  - HFiles are used to store real data (also include index data)

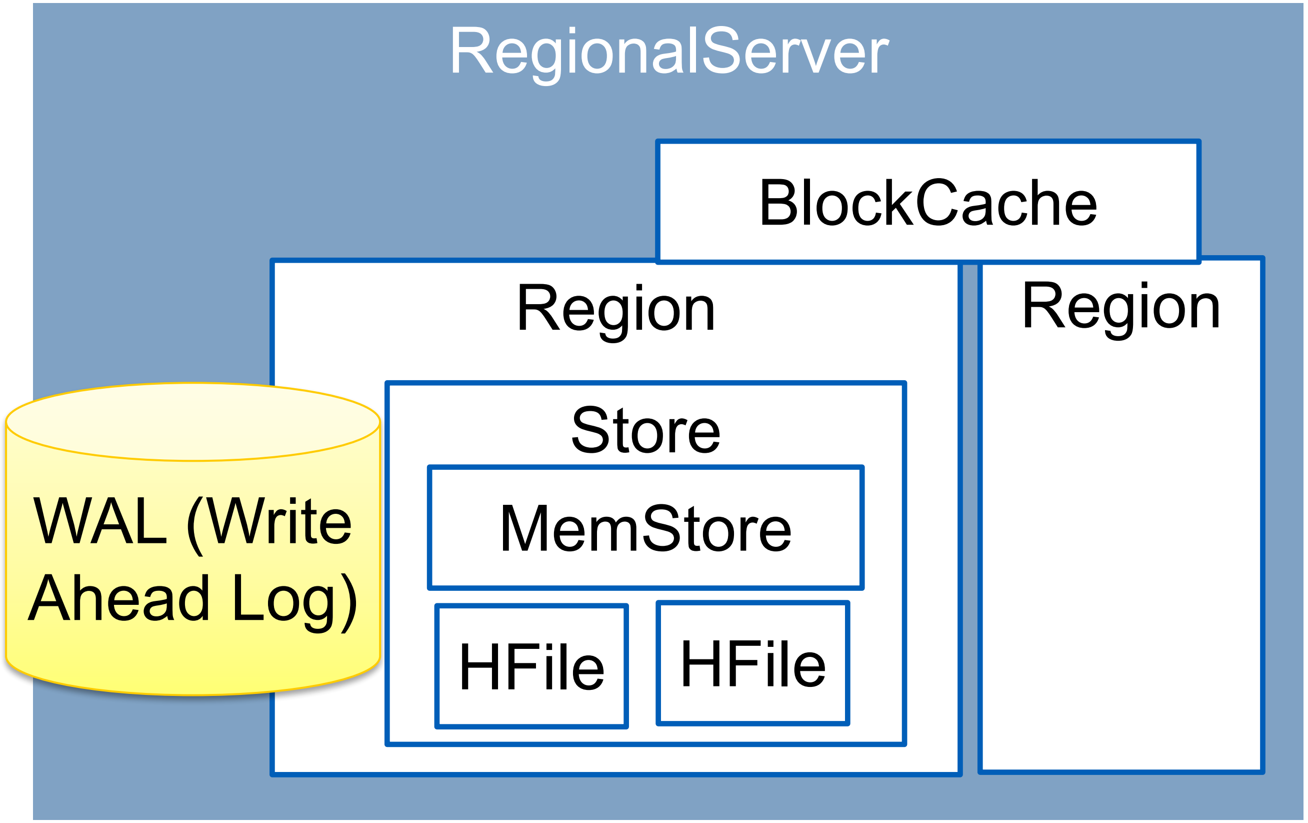
HBase architecture



Zookeeper:

- **shared state and failure notification of servers**
- **master address and recovery**

HBase architecture



MemStore: write cache for data in memory before written into files

BlockCache: for read cache

WAL is for durability

ACID

- **Atomic within a row**
- **Consistency**
  - can be programmed: e.g.,
    - read: STRONG (read performed by the primary region) and TIMELINE (primary region first, if not, then the secondary region)
- **Durability**
  - can be programmed
  - WAL (write ahead log)

Example of using HBase

Open Scalable Open Time Series Database (OpenTSDB)

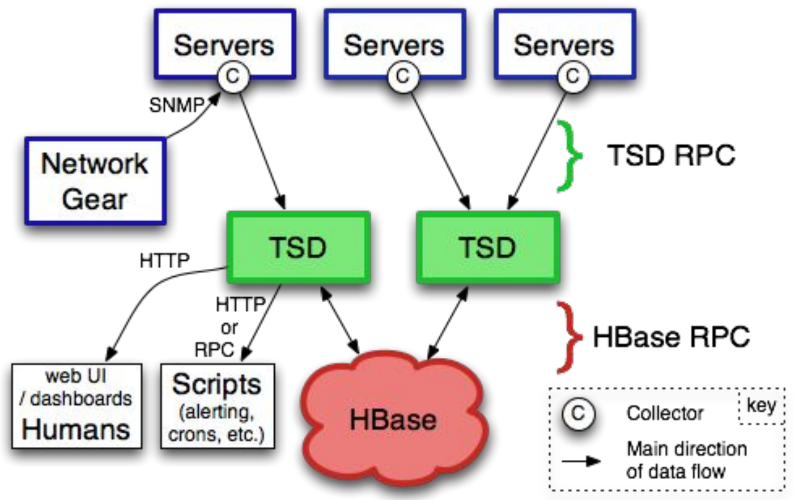


Figure source: http://opentsdb.net/overview.html

Salesforce

- **Salesforce Shield:** for supporting data security/compliance
- **Field Audit Trail:** for track changes
- **Event Monitoring:** log/event
- **Argus:** time series data and alerts

Source:
https://engineering.salesforce.com/investing-in-big-data-apache-hbase-420edfba2d30/

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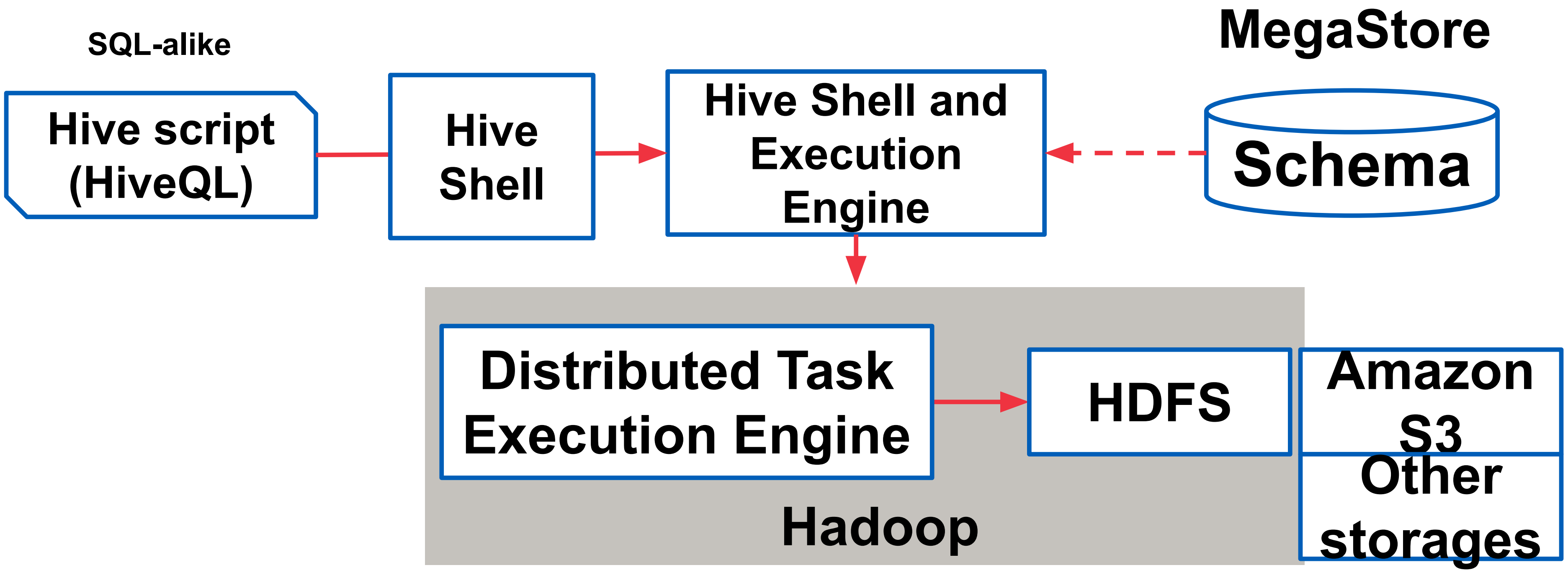
Apache Hive

Apache Hive

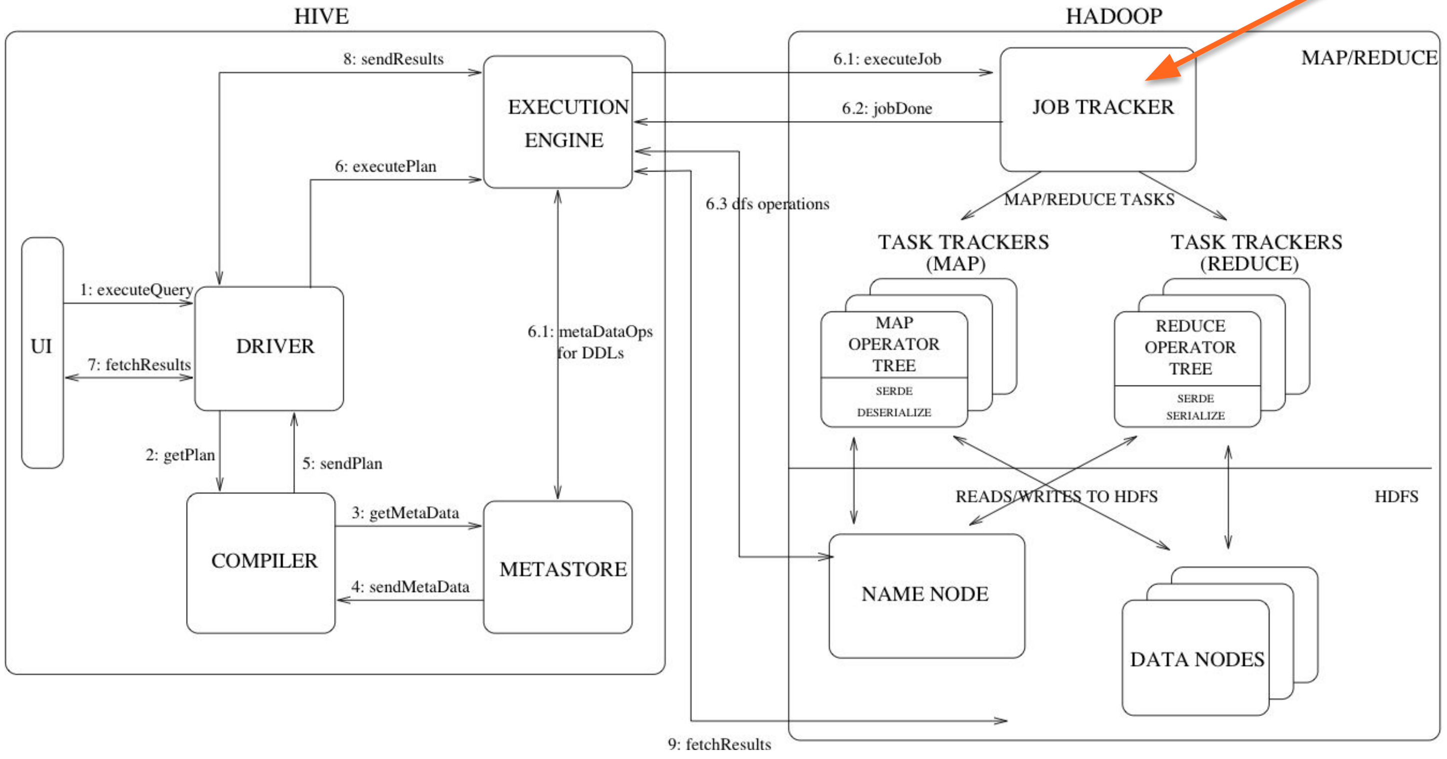
- **https://hive.apache.org/, on top of Hadoop**
  - data warehouse at a very large-scale
  - access data in large-scale storage like HDFS or S3
- **Support access to data via SQL styles**
  - extract/transform/load (ETL), reporting, and data analysis using SQL styles
- **Provide command line tools & JDBC and server for integration**

Reading – Hive in Facebook
https://engineering.fb.com/2009/06/10/web/hive-a-petabyte-scale-data-warehouse-using-hadoop/

High-level data flow language & programs



Hive building blocks



Distributed tasks with MapReduce, Tez (Workflow) or Spark

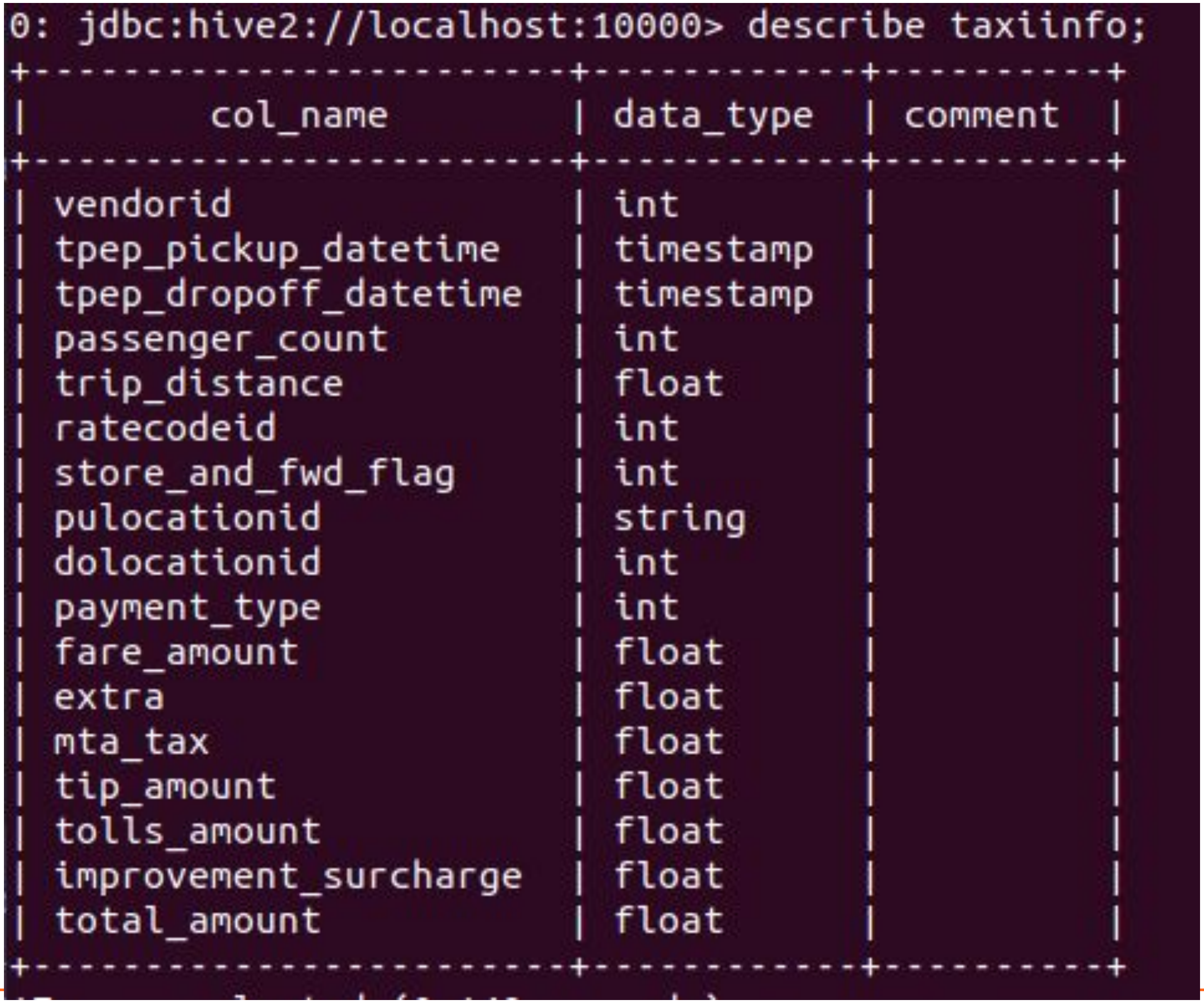
Figure source: https://cwiki.apache.org/confluence/display/Hive/Design

Hive data organization

- **Schema-on-read approach**
  - schema inferred from data, structured and unstructured data
- **Databases**
- **Table**
  - Managed table versus External tables
  - External table: real data is stored outside Hive and referenced so delete only table metadata but not the data (read data only)
  - Table is mapped to a directory in HDFS
- **Low-level files: CSV, Apache Parquet,ORC, …**
- **Managed vs External tables concept:**
  - also in BigQuery, Snowflake, Databricks Lakehouse

Example

Large tables lead to performance issues



```
0: jdbc:hive2://localhost:10000> describe taxiinfo;
+-------------------------+-------------+----------+
|        col_name         | data_type   | comment  |
+-------------------------+-------------+----------+
| vendorid                | int         |          |
| tpep_pickup_datetime    | timestamp   |          |
| tpep_dropoff_datetime   | timestamp   |          |
| passenger_count         | int         |          |
| trip_distance           | float       |          |
| ratecodeid              | int         |          |
| store_and_fwd_flag      | int         |          |
| pulocationid            | string      |          |
| dolocationid            | int         |          |
| payment_type            | int         |          |
| fare_amount             | float       |          |
| extra                   | float       |          |
| mta_tax                 | float       |          |
| tip_amount              | float       |          |
| tolls_amount            | float       |          |
| improvement_surcharge   | float       |          |
| total_amount            | float       |          |
+-------------------------+-------------+----------+
```

Hive data organization for performance optimization

- **Partitioning: using value of a column as a partitioning key**
  - partition keys determine how data in Table will be divided
    - *E.g. date or countries*
  - each partition is stored as a subdirectory
    - *Avoid many sub directories!*
- **Buckets: using a hash function of a column for grouping records into the same bucket**
  - avoid large number of small partitions
  - each bucket is stored in a file
  - bucket columns should be optimized for join/filter operations

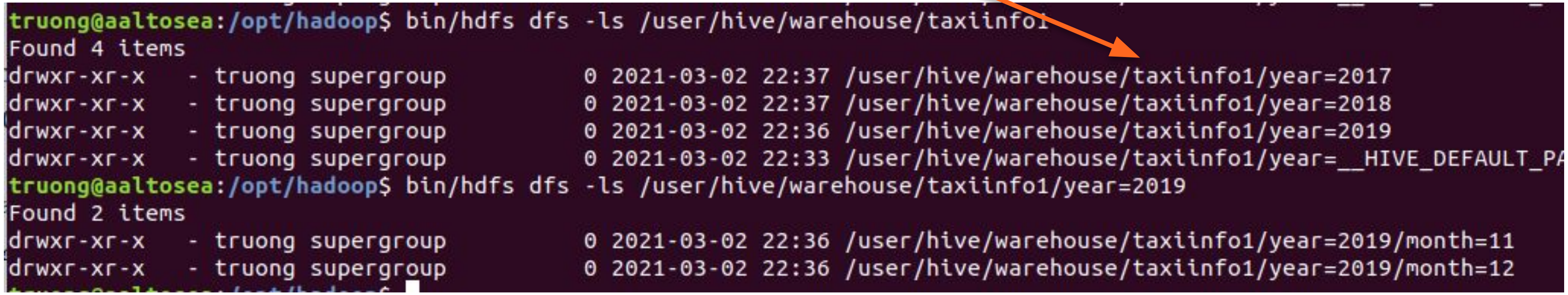
Example of partitions

```
CREATE TABLE taxiinfo1 ( ….)
 PARTITIONED BY  (year int, month int)
…;
```

Indicate partition info

Define partition names

```
LOAD DATA LOCAL INPATH …… INTO TABLE taxiinfo1
PARTITION (year=2019, month=11);
```

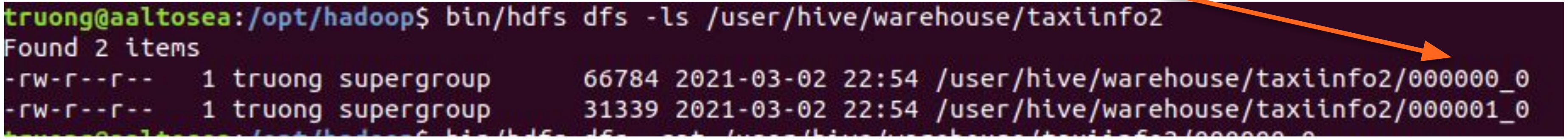


```
truong@aaltosea:/opt/hadoop$ bin/hdfs dfs -ls /user/hive/warehouse/taxiinfo1
Found 4 items
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:37 /user/hive/warehouse/taxiinfo1/year=2017
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:37 /user/hive/warehouse/taxiinfo1/year=2018
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:36 /user/hive/warehouse/taxiinfo1/year=2019
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:33 /user/hive/warehouse/taxiinfo1/year=__HIVE_DEFAULT_PA
truong@aaltosea:/opt/hadoop$ bin/hdfs dfs -ls /user/hive/warehouse/taxiinfo1/year=2019
Found 2 items
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:36 /user/hive/warehouse/taxiinfo1/year=2019/month=11
drwxr-xr-x   - truong supergroup          0 2021-03-02 22:36 /user/hive/warehouse/taxiinfo1/year=2019/month=12
```

Example of buckets

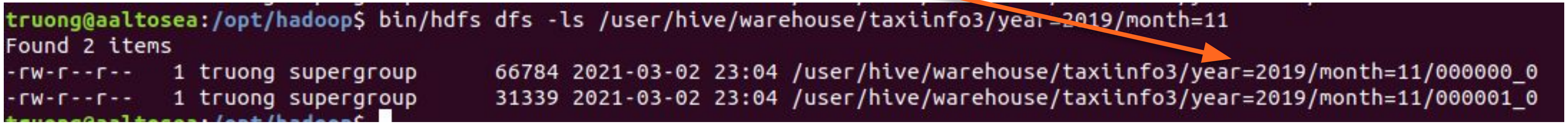
```
CREATE TABLE taxiinfo2 (VendorID int, ….)
 CLUSTERED BY (VendorID) INTO 2 BUCKETS
……;
```

Identify bucket column



```
truong@aaltosea:/opt/hadoop$ bin/hdfs dfs -ls /user/hive/warehouse/taxiinfo2
Found 2 items
-rw-r--r--   1 truong supergroup      66784 2021-03-02 22:54 /user/hive/warehouse/taxiinfo2/000000_0
-rw-r--r--   1 truong supergroup      31339 2021-03-02 22:54 /user/hive/warehouse/taxiinfo2/000001_0
```

Combine partitions with buckets



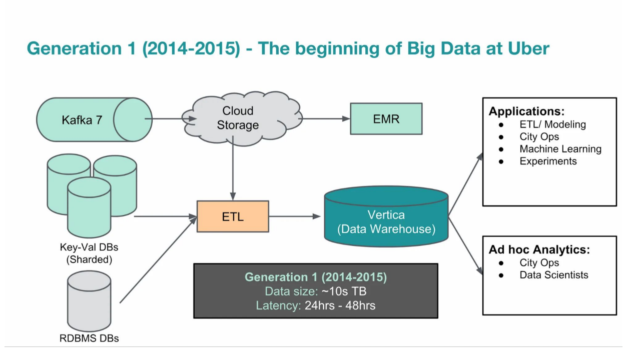
```
truong@aaltosea:/opt/hadoop$ bin/hdfs dfs -ls /user/hive/warehouse/taxiinfo3/year=2019/month=11
Found 2 items
-rw-r--r--   1 truong supergroup      66784 2021-03-02 23:04 /user/hive/warehouse/taxiinfo3/year=2019/month=11/000000_0
-rw-r--r--   1 truong supergroup      31339 2021-03-02 23:04 /user/hive/warehouse/taxiinfo3/year=2019/month=11/000001_0
```

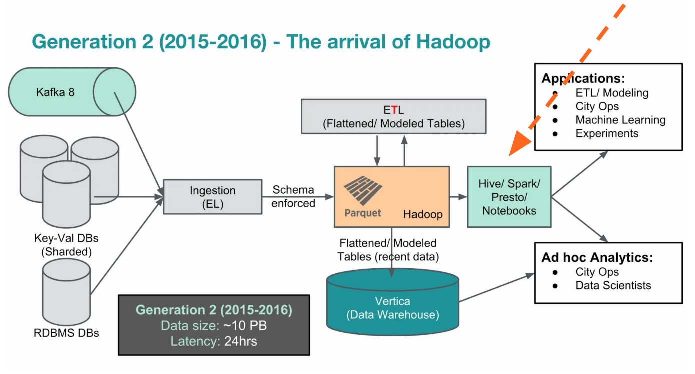
ACID

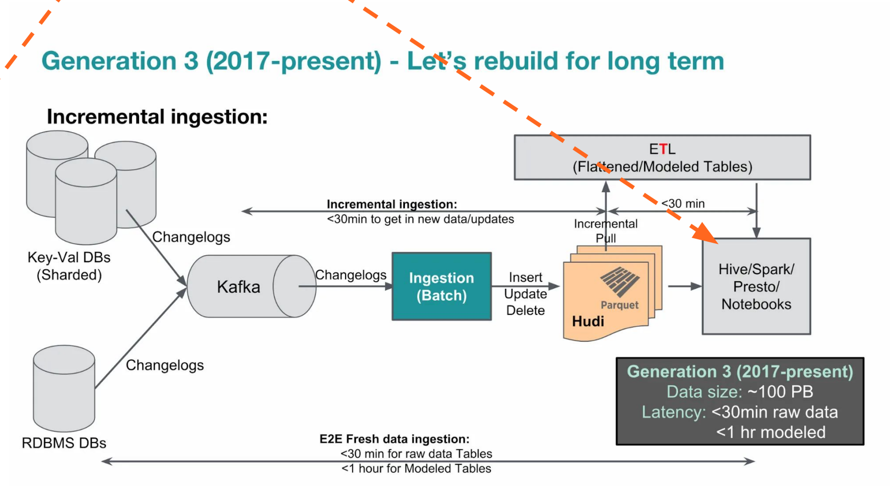
- **ACID support**
  - for managed tables
  - different for CRUD and insert-only tables
- **Locks are used for data isolation**
  - shared lock: for concurrent read of tables/partitions
  - exclusive lock: for modifying table/partition

Uber example

Hive for analytics: “extremely large queries”, “ “20,000 Hive queries per day” (see the source)







Generation 3 (2017-present) - Let’s rebuild for long term
Incremental ingestion:
ETL (Flattened/Modeled Tables)
Incremental ingestion:
<30min to get in new data/updates
<30 min
Incremental Pull
Key-Val DBs (Sharded)
Changelogs
Kafka
Changelogs
Ingestion (Batch)
Insert Update Delete
Parquet
Hudi
Hive/Spark/ Presto/ Notebooks
Changelogs
RDBMS DBs
Generation 3 (2017-present)
Data size: ~100 PB
Latency: <30min raw data
<1 hr modeled
E2E Fresh data ingestion:
<30 min for raw data Tables
<1 hour for Modeled Tables

Figures source:
https://www.uber.com/en-FI/blog/uber-big-data-platform/

Hive in the age of ML

- **Hive has been around for a while → many goals have been diminished**
- **But Hive Megastore continues an important role in data lakes and distributed data querying**
  - power data management and discovery
  - support unified data management
  - enable "feature store", discovery features used for machine learning

Summary

- **Hadoop software ecosystem is very powerful**
  - many applications and use cases have been developed
  - Hadoop File System (HDFS) is a crucial subject
- **Managed Hadoop ecosystem services by cloud providers**
  - try to look at Azure HDInsight, Google Dataproc, and Amazon EMR
- **High-level distributed query engineering using Hadoop components (HDFS, Hive)**
- **Understand the combination of data management with data processing techniques in the same system with Hadoop that simplify your big data tasks**

Thanks!

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rdsea.github.io