PA220: Database systems for data analytics

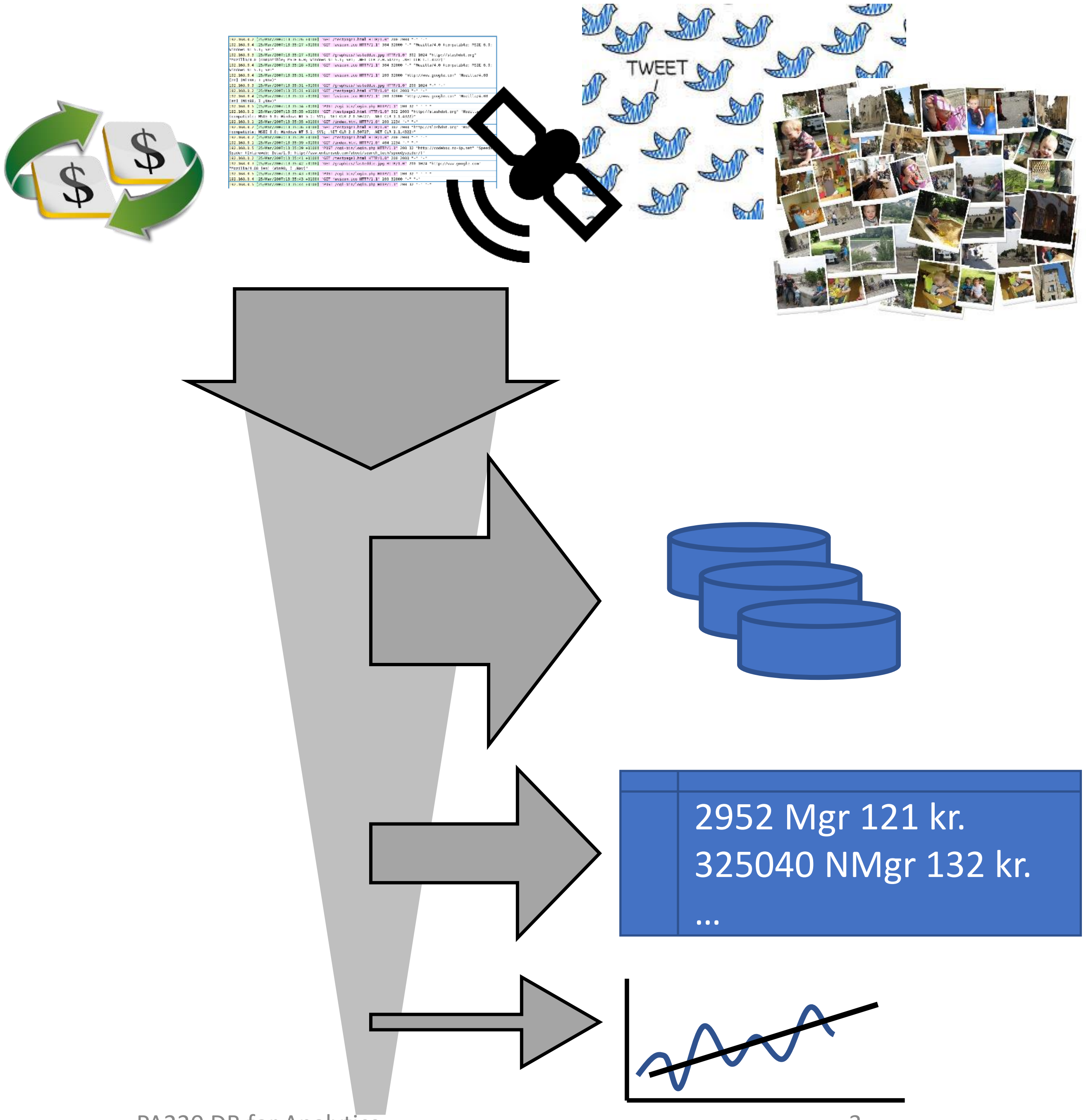
Big Data Analytics

Contents

- properties of current data
- architecture of data processing and analytics systems
- challenges in Big Data processing
- distributed data warehouse

Motivation

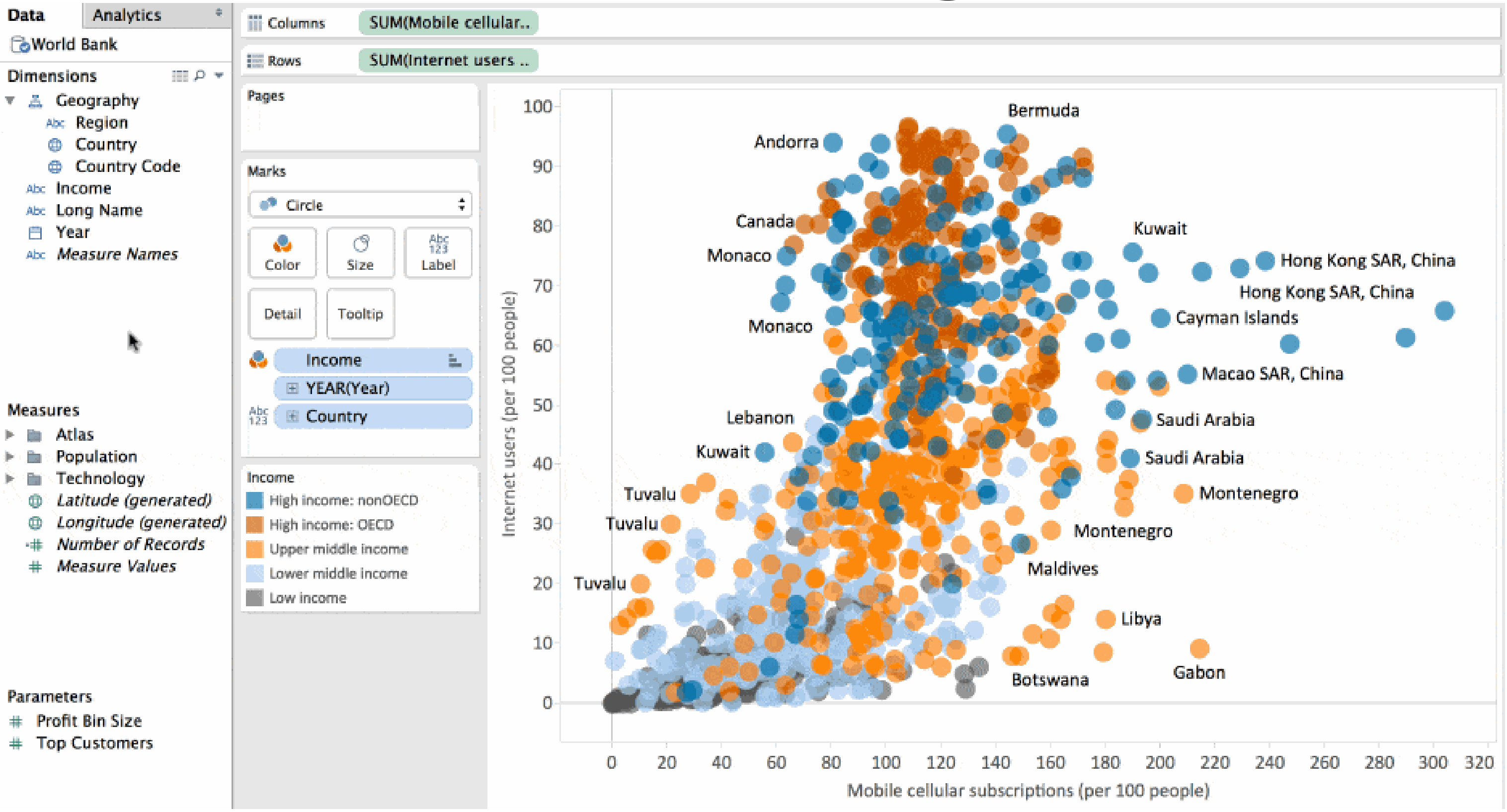
- Data production
  - Information systems
  - Monitoring services
  - Sensors, GPS tracking
  - Social networks
- Data processing
  - Storage & archiving
  - Summarization
  - Reporting
  - Visualization
  - Insights
  - Predictions



Nature of Current Data and Processing

Big Data

- Volume
  - the amount of data increases tenfold every five years
- Variety
  - varying data structure, text, multimedia, …
- Velocity
  - continuous data flow from sensors, social networks, …
- Veracity
  - with different data sources, it is getting more difficult to maintain data certainty

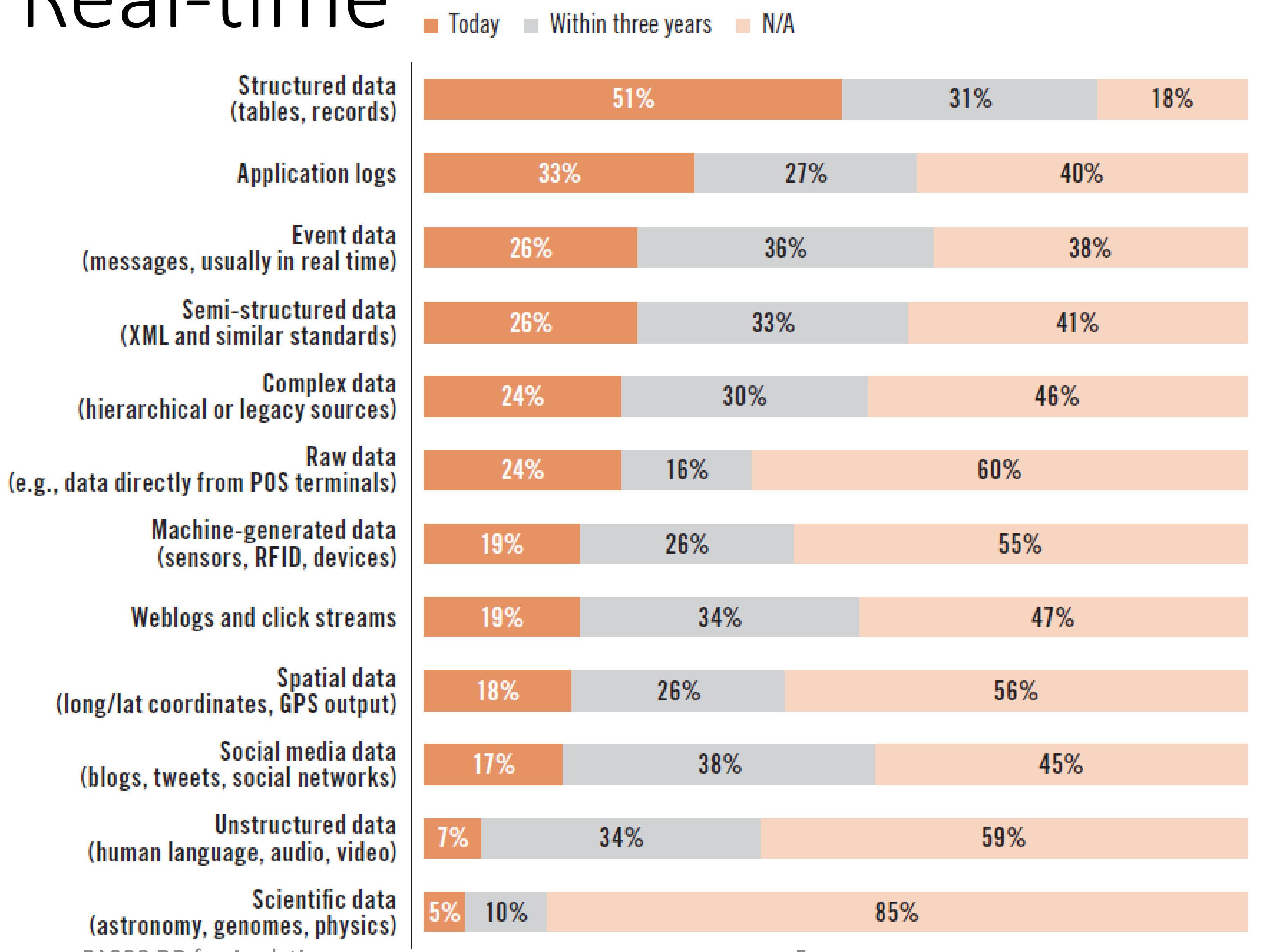


Source: tableau.com

- Real-time processing

Data Processed in Real-time

- TDWI report, Q4 2014
  - 105 companies over 500 emp.



Necessities for Big Data Analytics

- infrastructure for big data
  - processing
    - batch
    - stream (real-time)
  - storage
    - key-value stores
    - column stores
- algorithms for big data
  - data integration
  - data reporting
  - analytic functions
  - machine learning

Computational & Storage Opportunities

- horizontal scaling instead of vertical scaling
- new platforms
  - HDFS & MapReduce (e.g., Hadoop)
  - distributed stream processing (e.g., Storm)
  - column storage (e.g., Vertica)
  - NoSQL platforms (e.g., HBase)
  - in-memory DBMSs (e.g., VoltDB)

Hadoop Platform

- SW library for distributed processing of large data sets
  - across clusters of computers
- high-availability achieved on application layer by replication
  - tasks run / data stored on unreliable HW
- HDFS – distributed high-throughput file system
  - designed for mostly immutable files
  - concurrent write not supported
  - cooperation with MapReduce – data & computation locality
- MapReduce – programming model for large scale data processing
  - Map() – filtering and sorting, outputs “key,value” pairs
  - Reduce() – summarizing Map() results by their keys

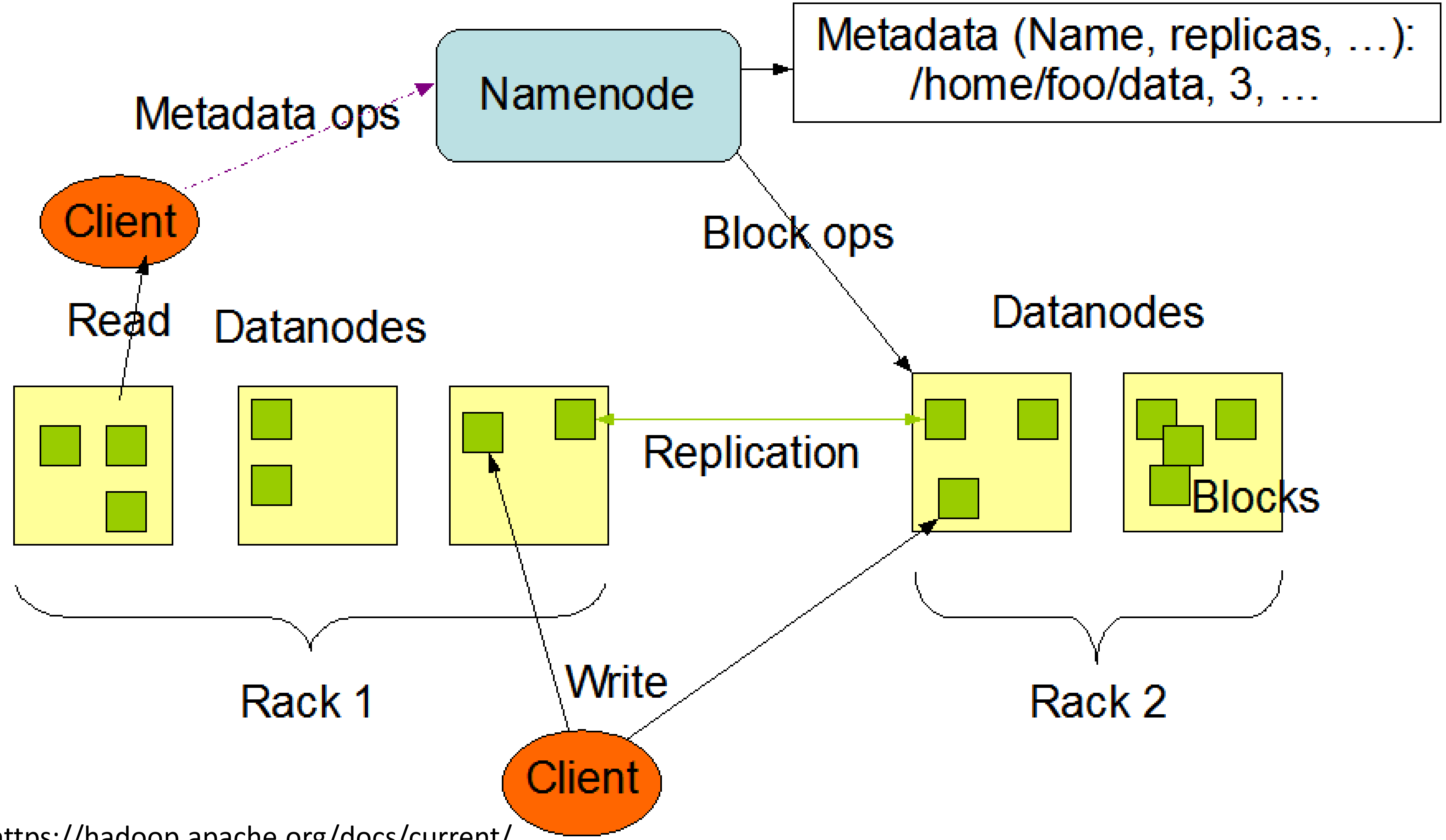
Map(k1,v1) → list(k2,v2)

Reduce(k2, list (v2)) → list(k3,v3)

HDFS

- Files are divided into blocks (chunks), typically 64 MB
  - The chunks are replicated at three different machines
    - ...in an “intelligent” fashion, e.g., never all on the same computer rack
  - The block size and replication factor are tunable per file.
- One machine is a name node (master)
- The others are data nodes (chunk servers)
  - The master keeps track of all file metadata
    - mappings from files to chunks and locations of the chunks on data nodes
  - To find a file chunk, the client queries the master, and then it contacts the relevant data nodes.
  - The master’s metadata files are also replicated.
- Files in HDFS are write-once (except for appends and truncates)
  - and have strictly one writer at any time.

HDFS Architecture



Source: https://hadoop.apache.org/docs/current/

Distributed Computation Platforms

- batch processing -> MapReduce, Spark, …
- stream processing -> Storm, Spark Streaming, …

- MapReduce
    - a programming model for distributed data processing
    - cooperates with a distributed file system

    - A distributed computational task has three phases:
        - The map phase: data transformation
        - The grouping phase done automatically by the MapReduce Framework
        - The reduce phase: data aggregation
    - The user defines only map & reduce functions.

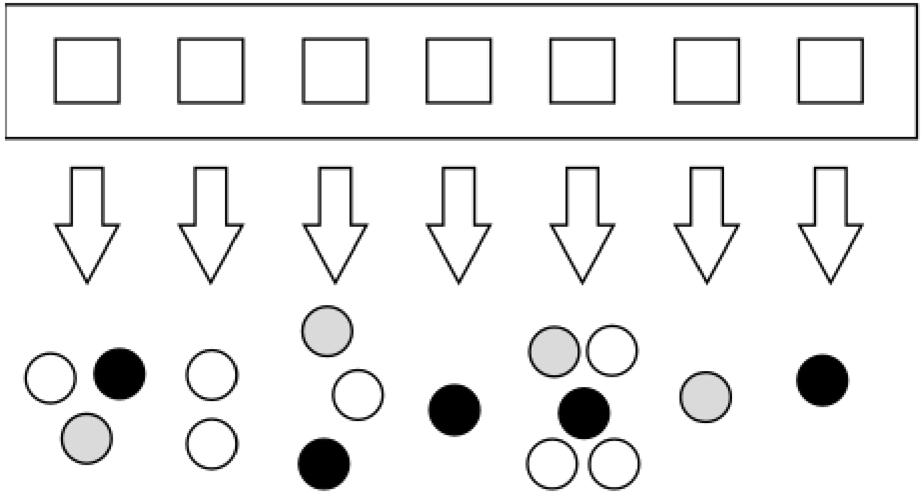
MapReduce – Map Function

- Map function simplifies the problem in this way:
  - Input: a single data item (e.g., line of text) from a data file
  - Output: zero or more (key, value) pairs

- The keys are not typical "primary keys":
  - They do not have to be unique
  - A map task can produce several key-value pairs with the same key (even from a single input)

- Map phase applies the map function to all items

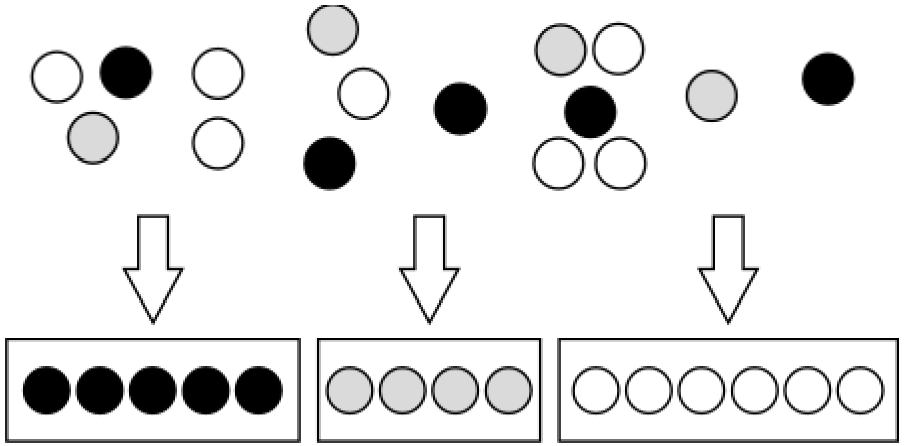
MapReduce – Map Function



- input data
- map function
- output data
  (color indicates the key value)

MapReduce – Grouping Phase

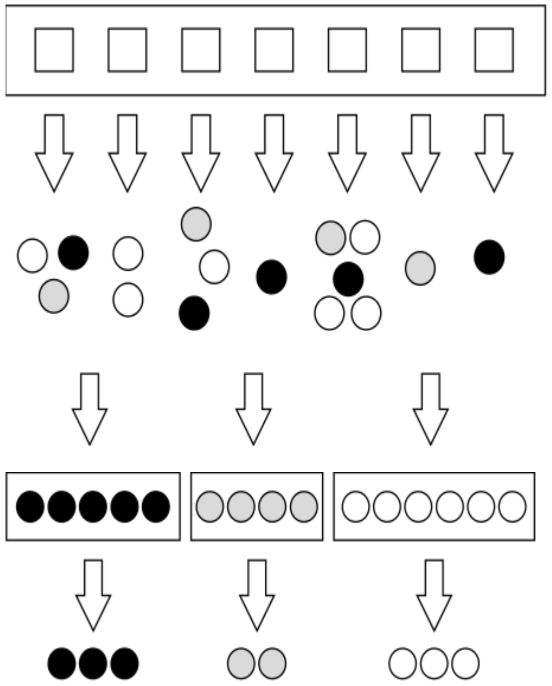
- Grouping (Shuffling): The key-value outputs from the map phase are grouped by key
  - Values sharing the same key are sent to the same reducer
  - These values are consolidated into a single list (key, list)
    - This is convenient for the reduce function
- This phase is realized by the MapReduce framework



- intermediate output
  (color indicates the key value)
- grouping phase – shuffle function

MapReduce – Reduce Function

- Reduce: combine the values for each key
  - to achieve the final result(s) of the computational task
- Input: (key, value-list)
  - value-list contains all values generated for given key in the Map phase
- Output: (key, value-list)
  - zero or more output records

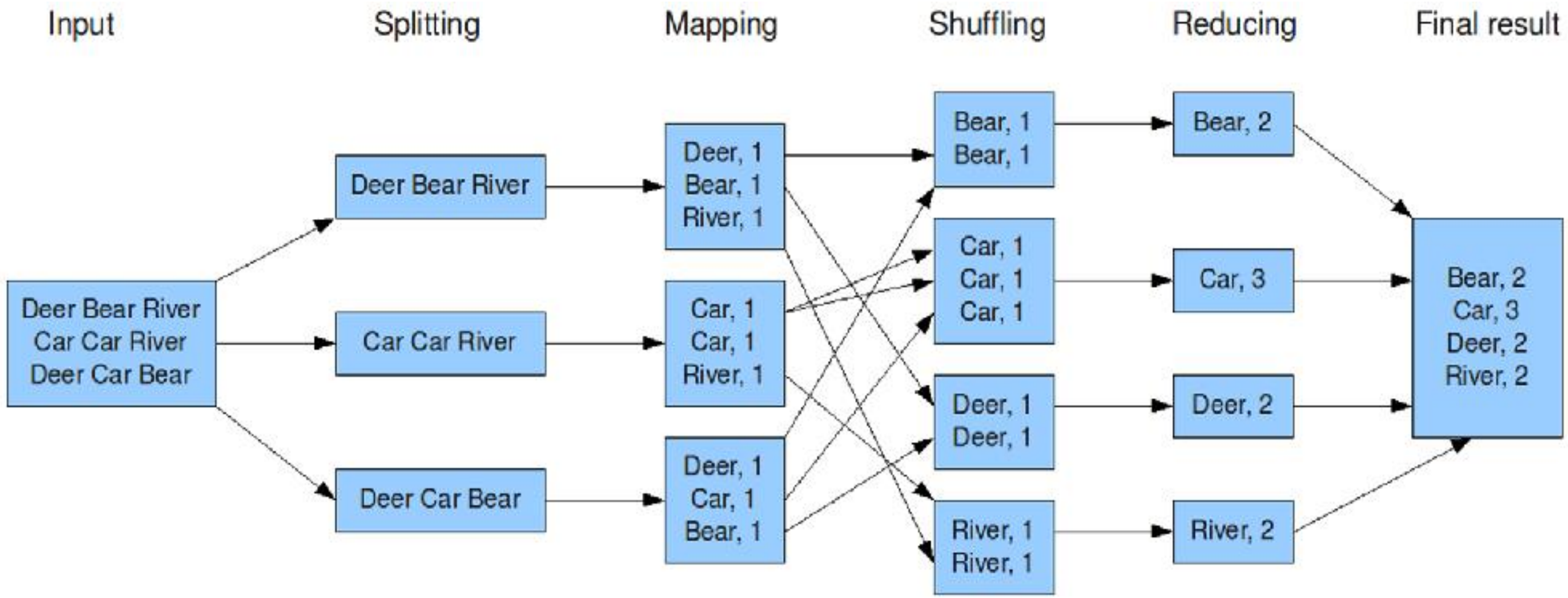


MapReduce Example: Word Count

- Task: Calculate word frequency in a set of documents

```
map(String key, Text value):
  // key: document name (ignored)
  // value: content of document (words)
foreach word w in value:
    emitIntermediate(w, 1);


reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
int result = 0;
foreach v in values:
    result += v;
emit(key, result);
```

MapReduce Example: Word Count

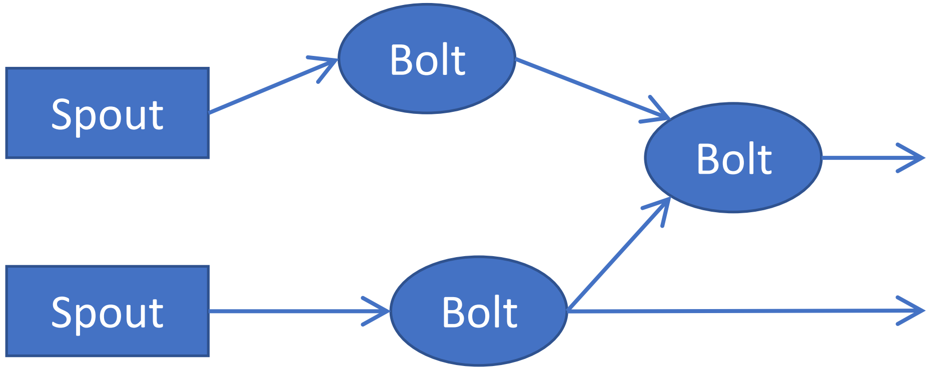


Source: http://www.cs.uml.edu/~jlu1/doc/source/report/MapReduce.html

Distributed Computation Platforms

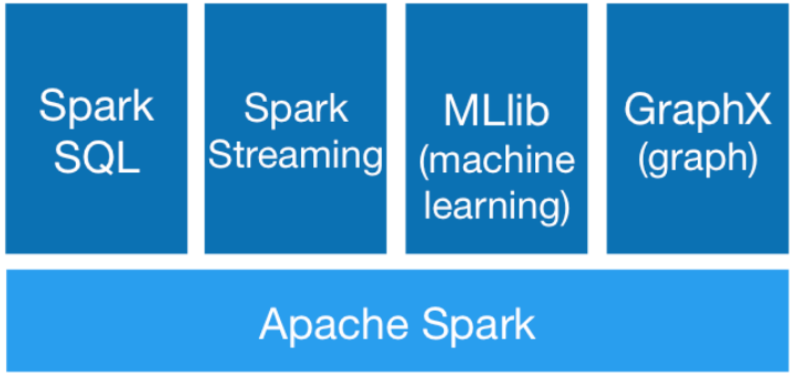
- batch processing -> MapReduce, Spark, …
- stream processing -> Storm, Spark Streaming, …

- Storm
  - real-time computation system, scalable, fault-tolerant
  - algorithm as a directed acyclic graph
    - edges = streams of data tuples
    - spouts = data source
    - bolts = processing node
  - data model = a tuple of named fields
  - mapping to physical workers



Apache Spark

- a unified analytics engine for large-scale data processing.
- high performance for both batch and streaming data
  - using a state-of-the-art DAG scheduler,
  - a query optimizer, and
  - a physical execution engine.
  - 100x faster than Hadoop



Distributed Storage Platforms

- key-value stores / NoSQL databases (Hbase)
  - structured / tabular data model, but flexible schema
  - horizontal scaling
  - no ACID, no join operation

  - key = identifies a row (typically with timestamp)
  - value = a multidimensional structure

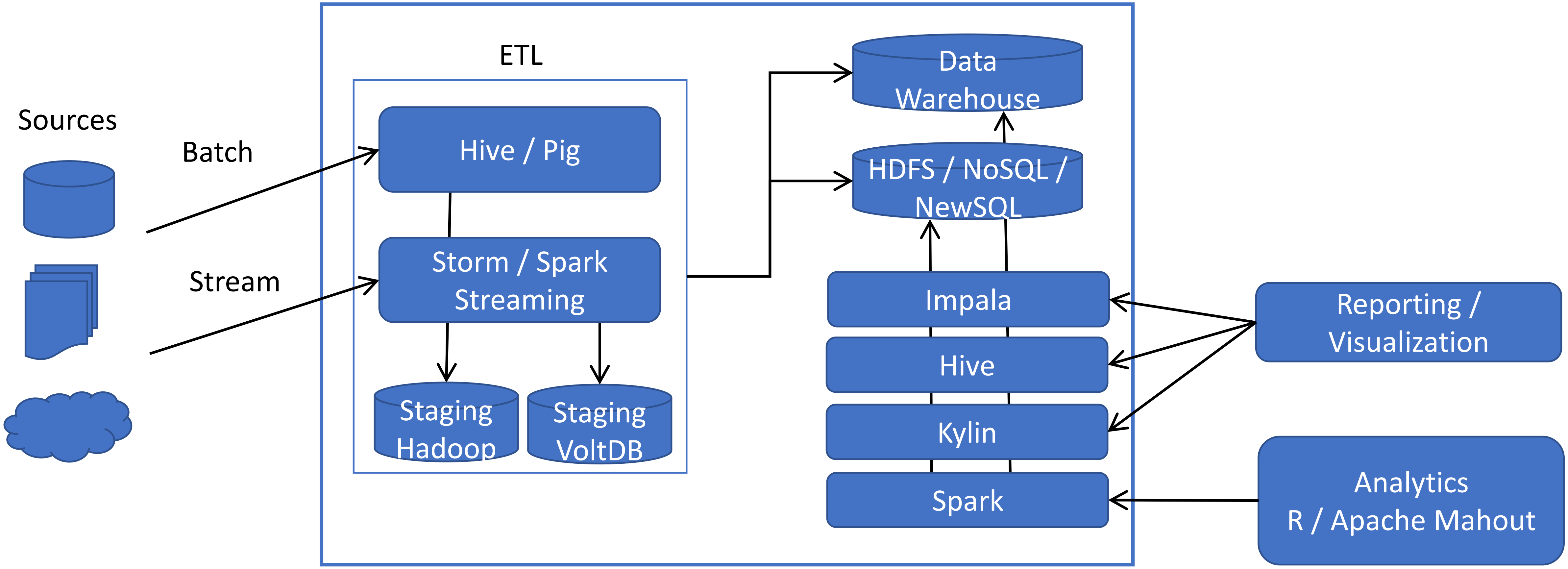
```
"aaaaa" : {
    "A" : {
      "foo" : "y",
      "bar" : "d"
    },
    "B" : {
      "" : "w"
    }
 }
```

- column stores (C-store)
  - relational data model, values of a column stored continuously
  - read-optimized, high-query throughput DBMS
  - relaxed consistency on reads

Distributed Storage Platforms

- real-time databases (e.g., VoltDB (originally H-Store))
  - NewSQL databases
    - scalability of NoSQL, relational data model
    - ACID guarantees
  - row-oriented storage on a distributed shared-nothing cluster
  - main memory db
  - fault-tolerance by node replication

Data Warehouse for Big Data



Distributed Data Warehouse

- Hive – data warehouse for large datasets
  - unstructured data in HDFS, structure projected on read
  - manages and queries data using HiveQL
    - converts them to Map-Reduce jobs
  - supports indexing
  - DML operations
    - UPDATE & DELETE at row level
- Kylin – provides OLAP for big data
  - precalculates aggregations – data cube on Hadoop and Spark
  - query engine translation
    - exploit prepared aggregations
    - low-latency query evaluation (sub-second)
  - integrate with Tableau, Power BI

Advanced Analytics

- Apache Mahout
  - scalable machine learning library
  - based on Hadoop, Spark
  - aimed at
    - recommendations, collaborative filtering
    - clustering, dimensionality reduction, classification
- Project R
  - platform for statistical computing and visualization
  - integrate to Hadoop

Advanced Analytics

- data quality is crucial
  - Tamr
    - data unification platform
    - automated integration with machine learning
    - thousands of data sources
- analytic model
  - computed & adjusted off-line
  - deployment
    - in complex analysis
    - in ETL

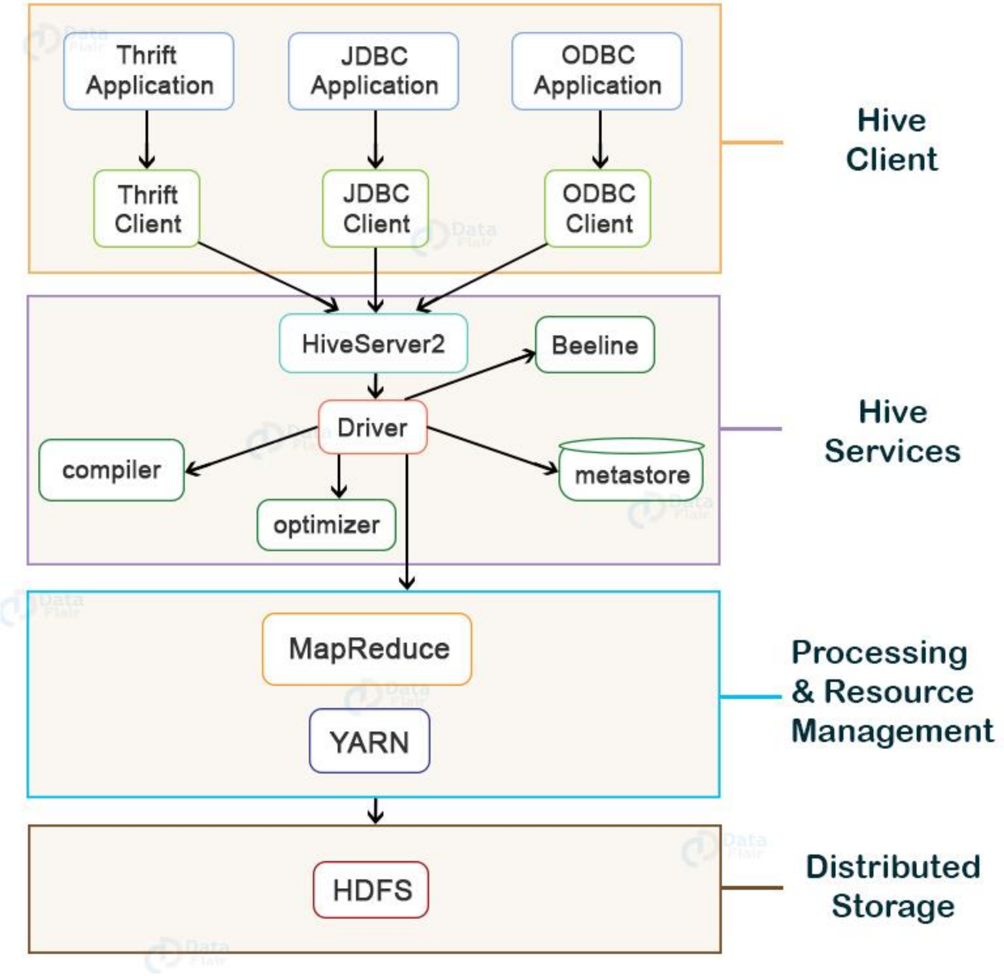
Advanced Analytics in Real-time

- event processing
  - tracking streams to detect events
  - event = change of state, exceeding a threshold, anomalies, …
  - deriving conclusions from events
- complex event processing
  - combine multiple sources
  - implement pattern detection, correlation, filtering, aggregation, …
  - extension to SQL – StreamSQL
    - continuous queries with incremental results
    - windowing & aggregations
    - windowing & joins

Apache Hive

- A system for querying and managing structured data built on top of Hadoop
  - Uses Map-Reduce for execution
  - HDFS for storage – but any system that implements Hadoop FS API
- Key Building Principles:
  - Structured data with rich data types (structs, lists and maps)
  - Directly query data from different formats (text/binary) and file formats (Flat/Sequence)
  - SQL as a familiar programming tool and for standard analytics
  - Allow embedded scripts for extensibility and for non-standard applications
  - Rich metadata to allow data discovery and for optimization

Apache Hive – Architecture



Source: https://data-flair.training/blogs/apache-hive-architecture/

Apache Hive – MetaStore

- Stores Table/Partition properties:
  - Table schema and SerDe library for formatting rows
  - Table Location on HDFS
  - Logical Partitioning keys and types
  - Partition level metadata
  - Other information

```
» CREATE TABLE mylog (
    user_id BIGINT,
    page_url STRING,
    unix_time INT)
  ROW FORMAT DELIMITED FIELDS TERMINATED BY '\t';

» CREATE table mylog_rc (
    user_id BIGINT,
    page_url STRING,
    unix_time INT)
  ROW FORMAT SERDE
    'org.apache.hadoop.hive.serde2.columnar.ColumnarSerDe'
  STORED AS RCFILE;
```

Apache Hive – Structured Data

- Type system
  - Primitive types (double, float, bigint, int, smallint, tinyint, boolean, string, timestamp)
  - Recursively build up using Composition/Maps/Lists
- ObjectInspector interface for user-defined types
  - To recursively list schema
  - To recursively access fields within a row object
- Generic (De)Serialization Interface (SerDe)
- Serialization families implement interface
  - Thrift DDL based SerDe
  - Delimited text based SerDe
  - You can write your own SerDe (XML, JSON …)

Apache Hive – Query Language

- Basic SQL
  - From clause subquery
  - ANSI JOIN (equi-join only)
  - Multi-table Insert
  - Multi group-by
  - Sampling
  - Objects traversal
- Extensibility
  - Pluggable Map-reduce scripts using TRANSFORM

```
hive> select * from temperature limit 10;
OK
stanice NULL    NULL    NULL    flag    NULL    NULL    NULL    stat    nazev
AQW00061705     1       1       1       26.888888888888893      P       -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       2       1       26.888888888888893      P       -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       3       1       26.833333333333332      P       -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       4       1       26.777777777777782      P       -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       5       1       26.777777777777782      P       -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       6       1       NULL            -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       7       1       NULL            -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       8       1       NULL            -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
AQW00061705     1       9       1       NULL            -14.3306        -170.7136       3.7     AS      PAGO PAGO WSO AP
Time taken: 0.293 seconds, Fetched: 10 row(s)

hive> describe temperature;
OK
stanice                 string
mesic                   int
den                     int
hodina                  int
teplota                 double
flag                    string
latitude                double
longitude               double
vyska                   double
stat                    string
nazev                   string
Time taken: 0.22 seconds, Fetched: 11 row(s)
```

Apache Hive – Query Language

- Aggregate queries mapped to MR jobs:

```
hive> select count(*) from temperature;
Query ID = dohnal_20210119140041_1a94796f-172f-4d40-b8c3-10932ea638c3
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
2021-01-19 14:00:41,609 INFO  [3093d28d-ea97-4e81-ab63-7c6cdd17fe7d main] client.ConfiguredRMFailoverProxyProvider: Failing over to rm2
Starting Job = job_1605005553005_4269, Tracking URL = https://hador-c1.ics.muni.cz:8090/proxy/application_1605005553005_4269/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1605005553005_4269
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 1
2021-01-19 14:00:50,401 Stage-1 map = 0%,  reduce = 0%
2021-01-19 14:01:01,721 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 6.07 sec
2021-01-19 14:01:13,029 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 8.2 sec
MapReduce Total cumulative CPU time: 8 seconds 200 msec
Ended Job = job_1605005553005_4269
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1  Reduce: 1   Cumulative CPU: 8.2 sec   HDFS Read: 8456014 HDFS Write: 107 HDFS EC Read: 0 SUCCESS
Total MapReduce CPU Time Spent: 8 seconds 200 msec
OK
4003322
Time taken: 32.929 seconds, Fetched: 1 row(s)
```

Apache Hive – Query Language

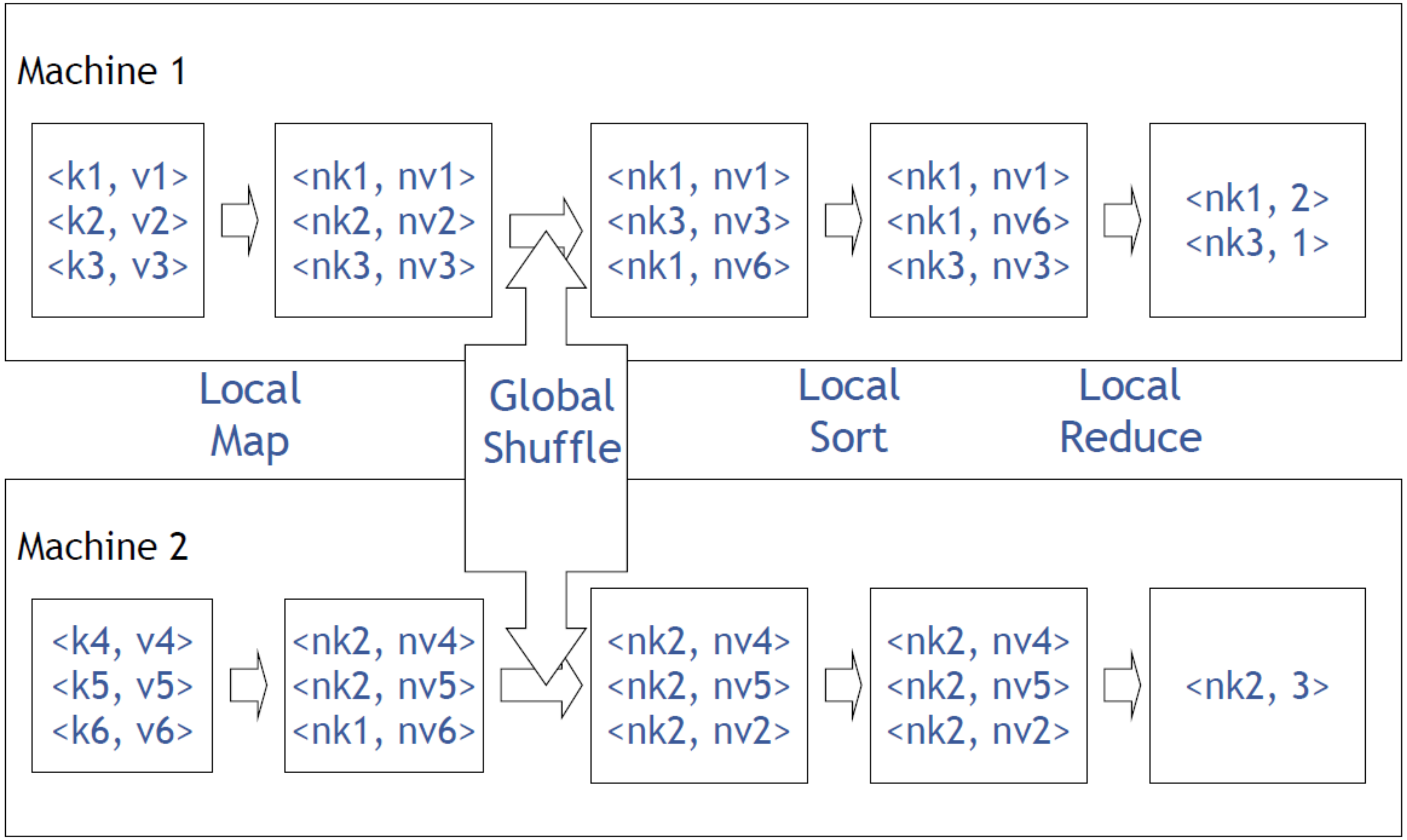
- Custom map/reduce scripts:

```
FROM (
  FROM pv_users
  SELECT TRANSFORM(pv_users.userid, pv_users.date) USING 'map_script' AS (dt, uid)
  CLUSTER BY(dt)
) map

INSERT INTO TABLE pv_users_reduced
  SELECT TRANSFORM(map.dt, map.uid) USING 'reduce_script' AS (day, count);
```

Sample map_script.py:

```
import sys
import datetime


for line in sys.stdin:
  line = line.strip()
  userid, unixtime = line.split('\t')
  weekday = datetime.datetime.fromtimestamp(float(unixtime)).isoweekday()
  print ','.join([str(weekday), userid])
```

Apache Hive – MapReduce



Apache Hive - HiveQL

- Joins – inner, outer
  - equi-joins with conjunctions supported

```
INSERT INTO TABLE pv_users
SELECT pv.pageid, u.age
FROM page_view pv JOIN user u ON (pv.userid = u.userid);

INSERT INTO TABLE pv_users
SELECT pv.*, u.gender, u.age
FROM page_view pv FULL OUTER JOIN user u ON (pv.userid = u.id)
WHERE pv.date = 2008-03-03;
```

- Group by

```
SELECT pageid, age, count(1)
FROM pv_users
GROUP BY pageid, age;

SELECT pageid, COUNT(DISTINCT userid)
FROM page_view GROUP BY pageid
```

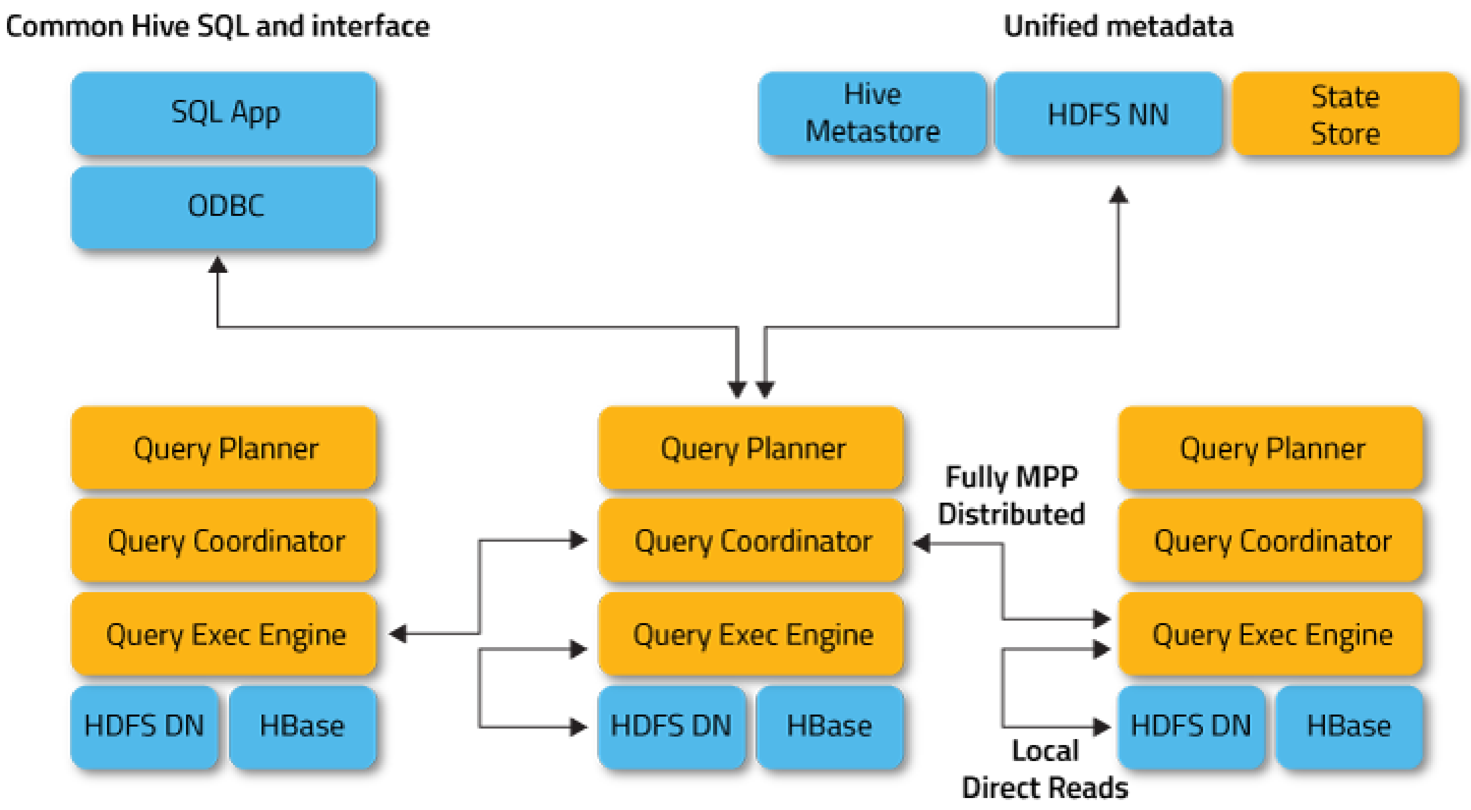
Apache Hive – Tables and Files

```
FROM pv_users

INSERT INTO TABLE pv_gender_sum
SELECT pv_users.gender, count_distinct(pv_users.userid)
GROUP BY(pv_users.gender)

INSERT INTO DIRECTORY ‘/user/facebook/tmp/pv_age_sum.dir’
SELECT pv_users.age, count_distinct(pv_users.userid)
GROUP BY(pv_users.age)

INSERT INTO LOCAL DIRECTORY ‘/home/me/pv_age_sum.dir’
FIELDS TERMINATED BY ‘,’ LINES TERMINATED BY \013
SELECT pv_users.age, count_distinct(pv_users.userid)
GROUP BY(pv_users.age);
```

Apache Impala

- a query engine that runs on Apache Hadoop
  - circumvents MapReduce to directly access the data
  - a specialized distributed query engine like commercial parallel RDBMSs
    - in C++, not Java; runtime code generation
- low-latency SQL queries to data stored in HDFS and Apache Hbase
  - an order-of-magnitude faster performance than Hive
- uses the same metadata, SQL syntax (HiveQL), ODBC driver, and user interface as Apache Hive
- supported storage formats
  - (compressed) text file, sequence file, RCFile, Avro, Parquet, HBase

Apache Impala – Architecture



Source: http://impala.apache.org/overview.html

Apache Impala – Query Language

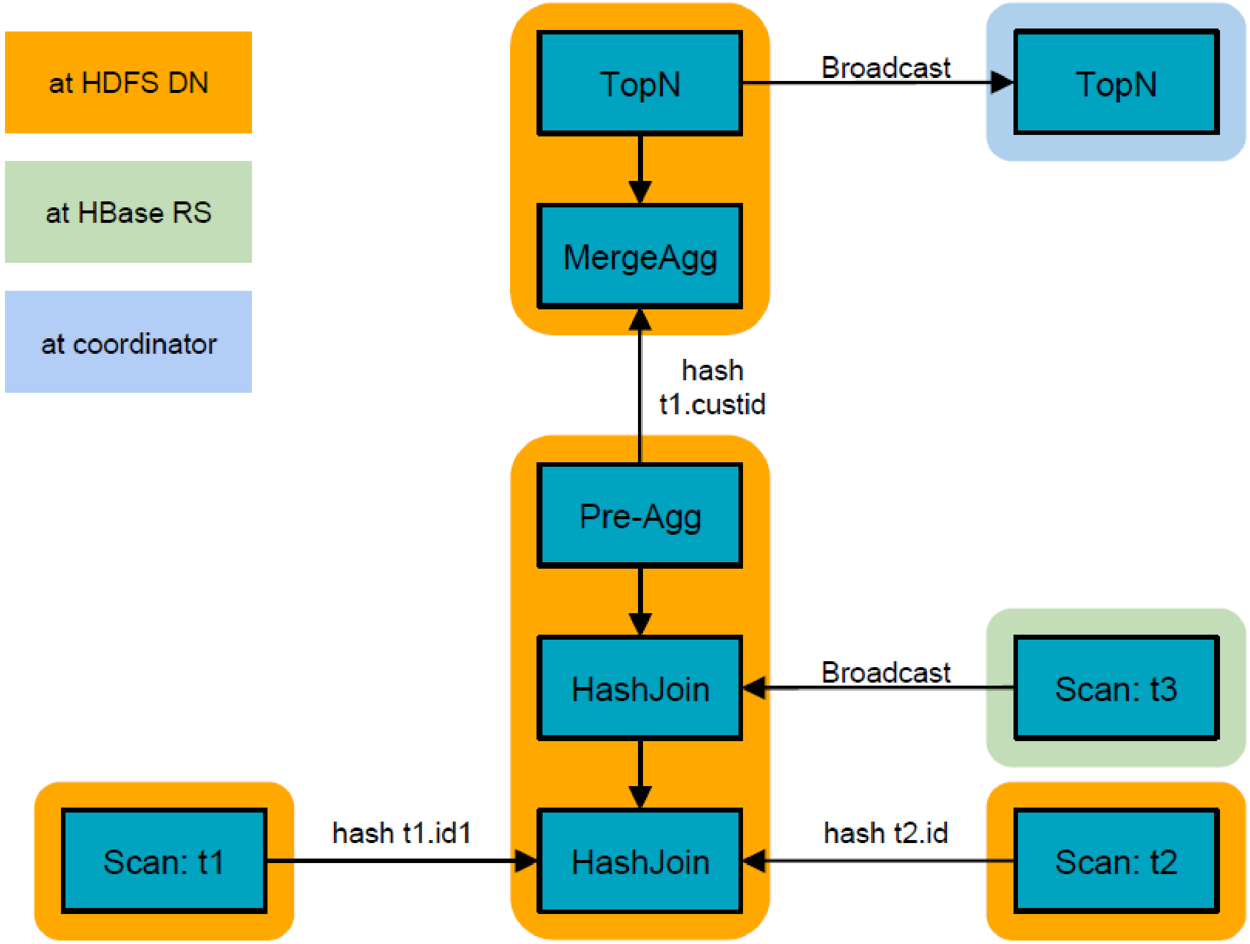
- SQL support:
    - essentially SQL-92, minus correlated subqueries
    - only equi-joins; no non-equi joins, no cross products
    - Order By requires Limit
    - (Limited) DDL support
    - SQL-style authorization via Apache Sentry (incubating)
    - UDFs and UDAFs are supported
- Join Limitation
    - The smaller table has to fit in aggregate memory of all executing nodes.

Apache Impala – Query Planning

- 2-phase planning process:
  - single-node plan: left-deep tree of plan operators
  - plan partitioning: partition single-node plan to maximize scan locality, minimize data movement
- Parallelization of operators:
  - All query operators are fully distributed.
- Plan operators:
  - Scan, HashJoin, HashAggregation, Union, TopN, Exchange

Apache Impala – Query Planning

```
SELECT t1.custid, SUM(t2.revenue) AS revenue
FROM LargeHdfsTable t1
   JOIN LargeHdfsTable t2 ON (t1.id1 = t2.id)
   JOIN SmallHbaseTable t3 ON (t1.id2 = t3.id)
WHERE t3.category = 'Online'
GROUP BY t1.custid
ORDER BY revenue DESC
LIMIT 10;
```



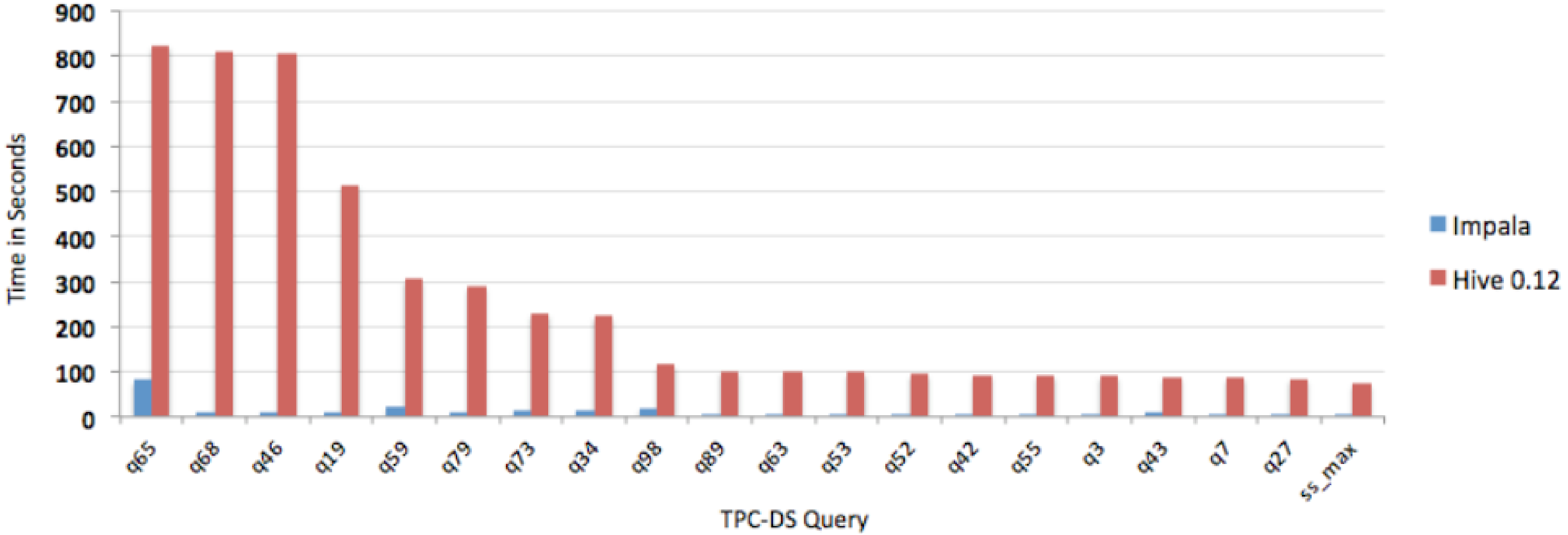
Apache Impala – Execution Engine

- Written in C++ for minimal execution overhead
- Internal in-memory tuple format
  - puts fixed-width data at fixed offsets
- Uses intrinsics/special cpu instructions
  - for text parsing, crc32 computation, etc.
- Runtime code generation for “big loops”
  - e.g., insert batch of rows into a hash table; unroll a loop that inlines all function calls, contains no dead code, minimizes branches
  - code generated using llvm

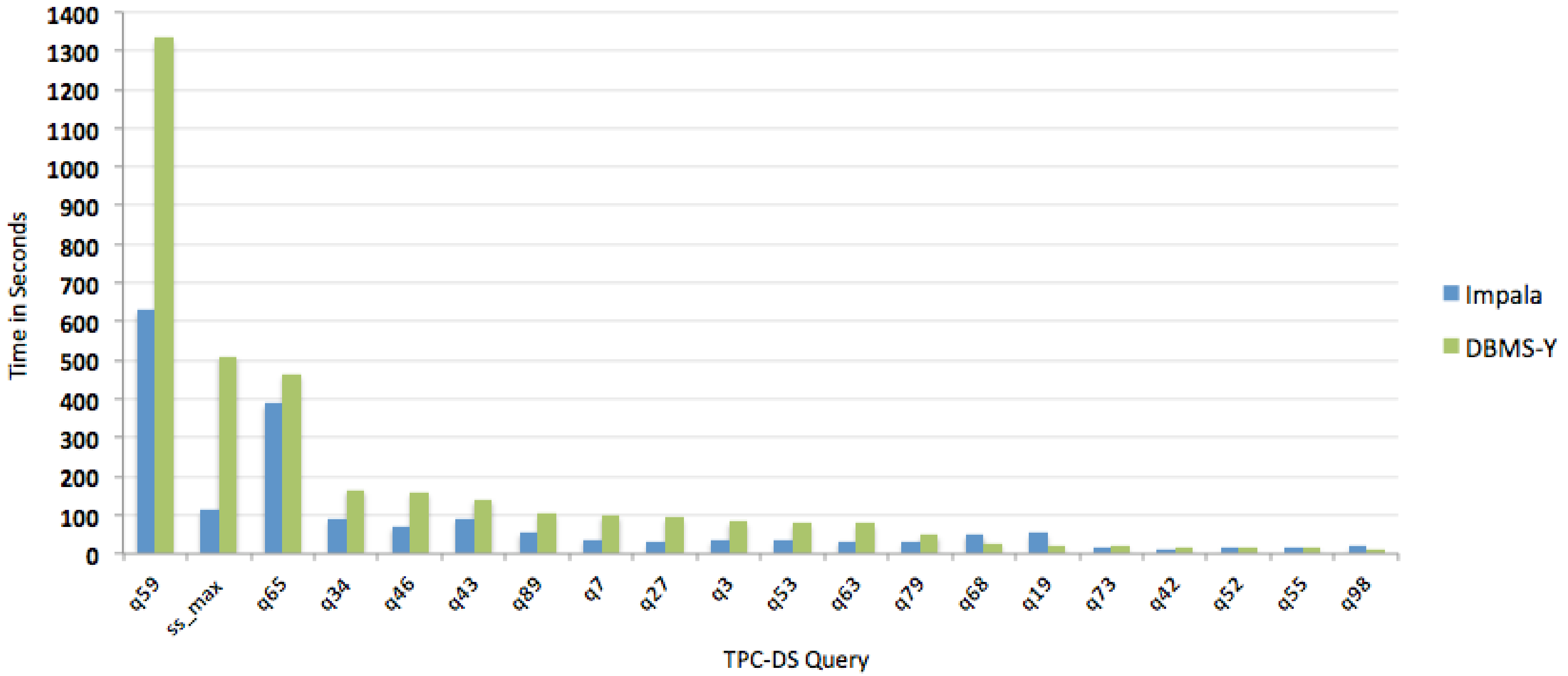
Apache Hive vs. Impala - Performance

- 20 pre-selected diverse TPC-DS queries
  - modified to remove unsupported language
- Sufficient data scale for realistic comparison (3 TB, 15 TB, and 30 TB)
- Realistic nodes (e.g., 8-core CPU, 96GB RAM, 12x2TB disks)
- Methodology - multiple runs, reviewed fairness for competition, …
- Results:
  - Impala vs Hive 0.12 (Impala 6--70x faster)
  - Impala vs “DBMS-Y” (Impala average of 2x faster)
  - Impala scalability (Impala achieves linear scale)

Apache Hive vs. Impala - Performance



Apache Hive vs. Impala - Performance



Apache Hive vs. Impala

	Hive	Impala
Design	MapReduce jobs	massively parallel processing (MPP)
Use case	long-running ETL jobs	low-latency/interactive queries, also for multi-user load; interactive BI experience
Complex data types	Yes	No
Query processing	disk-based	in-memory

Summary

- Big Data changes Data Warehousing to Distributed DWH
- Based on horizontally scalable frameworks
- Transition from batch processing (MR jobs) to stream processing (DAG of tasks)
- Query optimizers – special algorithms, in-memory processing,
- Real-time data processing and visualizations

Credits

- Hive Tutorial
  - https://cwiki.apache.org/confluence/display/Hive/Tutorial
- Facebook Data Team - HIVE: Data Warehousing & Analytics on Hadoop
  - https://slideshare.net/zshao/hive-data-warehousing-analytics-on-hadoop-presentation
- Mark Grover - Impala: A Modern, Open-Source SQL Engine for Hadoop
  - https://slideshare.net/markgrover/introduction-to-impala