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CS520
Data Integration, Warehousing, and Provenance

7. Big Data Systems and Integration

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Outline

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0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) **Big Data Analytics**
8) Data Provenance

3. Big Data Analytics

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- **Big Topic, big Buzzwords ;-)**
- Here
  - **Overview of two types of systems**
    - Key-value/document stores
    - **Mainly**: Bulk processing (MR, graph, …)
  - **What is new compared to single node systems?**
  - **How do these systems change our approach to integration/analytics**
    - Schema first vs. Schema later
    - **Pay-as-you-go**

3. Big Data Overview

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- **1) How does data processing at scale (read using many machines) differ from what we had before?**
  - Load-balancing
  - Fault tolerance
  - Communication
  - New abstractions
    - Distributed file systems/storage

3. Big Data Overview

- **2) Overview of systems and how they achieve scalability**
  - **Bulk processing**
    - MapReduce, Shark, Flink, Hyracks, …
    - Graph: e.g., Giraph, Pregel, …
  - **Key-value/document stores = NoSQL**
    - Cassandra, MongoDB, Memcached, Dynamo, …

3. Big Data Overview

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- **2) Overview of systems and how they achieve scalability**
  - **Bulk processing**
    - MapReduce, Shark, Flink,
  - **Fault tolerance**
    - Replication
    - Handling stragglers
  - **Load balancing**
    - Partitioning
    - Shuffle

3. Big Data Overview

- **3) New approach towards integration**
  - **Large clusters enable directly running queries over semi-structured data (within feasible time)**
    - Take a click-stream log and run a query
  - One of the reasons why **pay-as-you-go** is now feasible
    - **Previously:** designing a database schema upfront and designing a process (e.g., ETL) for cleaning and transforming data to match this schema, then query
    - **Now:** start analysis directly, clean and transform data if needed for the analysis

3. Big Data Overview

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- **3) New approach towards integration**
  - **Advantage of pay-as-you-go**
    - More timely data (direct access)
    - More applicable if characteristics of data change dramatically (e.g., yesterdays ETL process no longer applicable)
  - **Disadvantages of pay-as-you-go**
    - Potentially repeated efforts (everybody cleans the click-log before running the analysis)
    - Lack of meta-data may make it hard to
      - Determine what data to use for analysis
      - Hard to understand semantics of data

- **Scalable systems**
  - Performance of the system scales in the number of nodes
    - Ideally the per node performance is constant independent of how many nodes there are in the system
    - This means: having twice the number of nodes would give us twice the performance
  - Why scaling is important?
    - If a system scales well we can “throw” more resources at it to improve performance and this is cost effective

- **What impacts scaling?**
  - Basically how parallelizable is my algorithm
    - **Positive example**: problem can be divided into subproblems that can be solved independently without requiring communication
      - E.g., array of 1-billion integers [i_1, …, $i_{1,000,000,000}$] add 3 to each integer. Compute on n nodes, split input into n equally sized chunks and let each node process one chunk
    - **Negative example**: problem where subproblems are strongly intercorrelated
      - E.g., Context Free Grammar Membership: given a string and a context free grammar, does the string belong to the language defined by the grammar.

3. Big Data – Processing at Scale

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- **New problems at scale**
  - DBMS
    - running on 1 or 10's of machines
    - running on 1000's of machines
- Each machine has low probability of failure
  - If you have many machines, failures are the norm
  - Need mechanisms for the system to cope with failures
    - Do not loose data
    - Do not use progress of computation when node fails
  - This is called **fault-tolerance**

3. Big Data – Processing at Scale

- **New problems at scale**
  - DBMS
    - running on 1 or 10’s of machines
    - running on 1000’s of machines
- Each machine has limited storage and computational capabilities
  - Need to **evenly** distribute data and computation across nodes
    - Often most overloaded node determine processing speed
  - This is called **load-balancing**

3. Big Data – Processing at Scale

- **Building distributed systems is hard**
  - Many pitfalls
    - Maintaining distributed state
    - Fault tolerance
    - Load balancing
  - Requires a lot of background in
    - OS
    - Networking
    - Algorithm design
    - Parallel programming

- **Building distributed systems is hard**
  - Hard to debug
    - Even debugging a parallel program on a single machine is already hard
      - Non-determinism because of scheduling: Race conditions
      - In general hard to reason over behavior of parallel threads of execution
    - Even harder when across machines
  - Just think about how hard it was for you to first program with threads/processes

3. Big Data – Why large scale?

- **Datasets are too large**
  - **Storing a 1 Petabyte dataset requires 1 PB storage**
    - **Not possible on single machine even with RAID storage**
- **Processing power/bandwidth of single machine is not sufficient**
  - **Run a query over the facebook social network graph**
    - **Only possible within feasible time if distributed across many nodes**

3. Big Data – User’s Point of View

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- **How to improve the efficiency of distributed systems experts**
  - Building a distributed system from scratch for every store and analysis task is obviously not feasible!
- **How to support analysis over large datasets for non distributed systems experts**
  - How to enable somebody with some programming but limited/no distributed systems background to run distributed computations

3. Big Data – Abstractions

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- **Solution**
  - Provide higher level abstractions
- **Examples**
  - **MPI** (message passing interface)
    - Widely applied in HPC
    - Still quite low-level
  - **Distributed file systems**
    - Make distribution of storage transparent
  - **Key-value storage**
    - Distributed store/retrieval of data by identifier (key)

3. Big Data – Abstractions

- **More Examples**
  - **Distributed table storage**
    - Store relations, but no SQL interface
  - **Distributed programming frameworks**
    - Provide a, typically, limited programming model with automated distribution
  - **Distributed databases, scripting languages**
    - Provide a high-level language, e.g., SQL-like with an execution engine that is distributed

3. Distributed File Systems

- **Transparent distribution of storage**
  - Fault tolerance
  - Load balancing?
- **Examples**
  - **HPC distributed filesystems**
    - Typically assume a limited number of dedicated storage servers
    - GPFS, Lustre, PVFS
  - **"Big Data" filesystems**
    - Google file system, HDFS

3. HDFS

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- **Hadoop Distributed Filesystem (HDFS)**
- Architecture
  - One nodes storing metadata (name node)
  - Many nodes storing file content (data nodes)
- Filestructure
  - Files consist of blocks (e.g., 64MB size)
- Limitations
  - Files are append only

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- **Name node**
- Stores the directory structure
- Stores which blocks belong to which files
- Stores which nodes store copies of which block
- Detects when data nodes are down
  - Heartbeat mechanism

- Clients communicate with the name node to gather FS metadata

3. HDFS

- **Data nodes**
- Store blocks
- Send/receive file data from clients
- Send heart-beat messages to name node to indicate that they are still alive

- Clients communicate with data nodes for reading/writing files

- **Fault tolerance**
  - n-way replication
  - Name node detects failed nodes based on heart-beats
  - If a node if down, then the name node schedules additional copies of the blocks stored by this node to be copied from nodes storing the remaining copies

3. Distributed FS Discussion

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- **What do we get?**
  - Can store files that do not fit onto single nodes
  - Get fault tolerance
  - Improved read speed (caused by replication)
  - Decreased write speed (caused by replication)
- **What is missing?**
  - Computations
  - Locality (horizontal partitioning)
  - Updates
- **What is not working properly?**
  - Large number of files (name nodes would be overloaded)

3. Frameworks for Distributed Computations

- **Problems**
  - Not all algorithms do parallelize well
  - How to simplify distributed programming?
- **Solution**
  - Fix a reasonable powerful, but simple enough model of computation for which scalable algorithms are known
  - Implement distributed execution engine for this model and make it fault tolerant and load-balanced

- **Data Model**
  - Sets of key-value pairs $\{(k_1,v_1), \ldots, (k_n,v_n)\}$
  - **Key** is an identifier for a piece data
  - **Value** is the data associaed with a key
- **Programming Model**
  - We have two higher-level functions **map** and **reduce**
    - Take as input a user-defined function that is applied to elements in the input key-value pair set
  - Complex computations can be achieved by chaining map-reduce computations

3. MapReduce Datamodel

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- **Data Model**
  - Sets of key-value pairs $\{(k_1,v_1), \ldots, (k_n,v_n)\}$
  - **Key** is an identifier for a piece data
  - **Value** is the data associaed with a key
- **Examples**
  - Document **d** with an **id**
    - (id, d)
  - Person with name, salary, and SSN
    - (SSN, "name, salary")

- **Map**
  - Takes as input a set of key-value pairs and a user-defined function `f:(k,v) -> {(k,v)}`
  - Map applies f to every input key-value pair and returns the union of the outputs produced by f

$\{(k_1,v_1),\ldots,(k_n,v_n)\}$

$\rightarrow$

$f((k_1,v_1)) \cup \ldots \cup f((k_n,v_n))$

- **Example**
  - **Input**: Set of (city,population) pairs
  - **Task**: multiply population by 1.05
- **Map function**
  - `f: (city,population) -> {(city,population*1.05)}`
- Application of f through map
  - Input: `{(chicago, 3), (nashville, 1)}`
  - Output: `{(chicago, 3.15)} ∪ {(nashville, 1.05)}`
    `= {(chicago, 3.15), (nashville, 1.05)}`

- **Reduce**
  - Takes as input a key with a list of associated values and a user-defined function

    `g: (k,list(v)) -> {(k,v)}`

  - Reduce groups all values with the same key in the input key-value set and passes each key and its list of values to **g** and returns the union of the outputs produced by **g**

$\{(k_1,v_{11}),\ldots,(k_1,v_{1n1}),\ \ldots\ (k_m,v_{m1}),\ldots,(k_m,v_{mnm})\}$

$\rightarrow$

$g((k_1,(v_{11},\ldots,v_{1n1}))\ \cup\ \ldots\ \cup\ g((k_m,(v_{m1},\ldots,v_{mnm}))$

3. MapReduce Computational Model

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- **Example**
  - **Input**: Set of (state, population) pairs one for each city in the state
  - **Task**: compute the total population per state
- **Reduce function**
  - `g: (state,[p₁, …, pₙ]) -> {(state,SUM([p₁,…,pₙ])}`
- Application of g through reduce
  - Input: `{(illinois, 3), (illinois, 1), (oregon, 15)}`
  - Output: `{(illinois, 4), (oregon, 15)}`

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- **Workflows**
  - Computations in MapReduce consists of map phases followed by reduce phases
    - The input to the reduce phase is the output of the map phase
  - Complex computations may require multiple map-reduce phases to be chained together

3. MapReduce Implementations

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- **MapReduce**
  - Developed by google
  - Written in C
  - Runs on top of GFS (Google's distributed filesystem)
- **Hadoop**
  - Open source Apache project
  - Written in Java
  - Runs on-top of HDFS

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- **Anatomy of a Hadoop cluster**
  - **Job tracker**
    - Clients submit MR jobs to the job tracker
    - Job tracker monitors progress
  - **Task tracker aka workers**
    - Execute map and reduce jobs
- **Job**
  - **Input**: files from HDFS
  - **Output**: written to HDFS
  - Map/Reduce UDFs

- **Fault tolerance**
  - **Handling stragglers**
    - Job tracker will reschedule jobs to a different worker if the worker falls behind too much with processing
  - **Materialization**
    - Inputs are read from HDFS
    - Workers write results of map jobs assigned to them to local disk
    - Workers write results of reduce jobs to HDFS for persistence

3. Hadoop – MR Job

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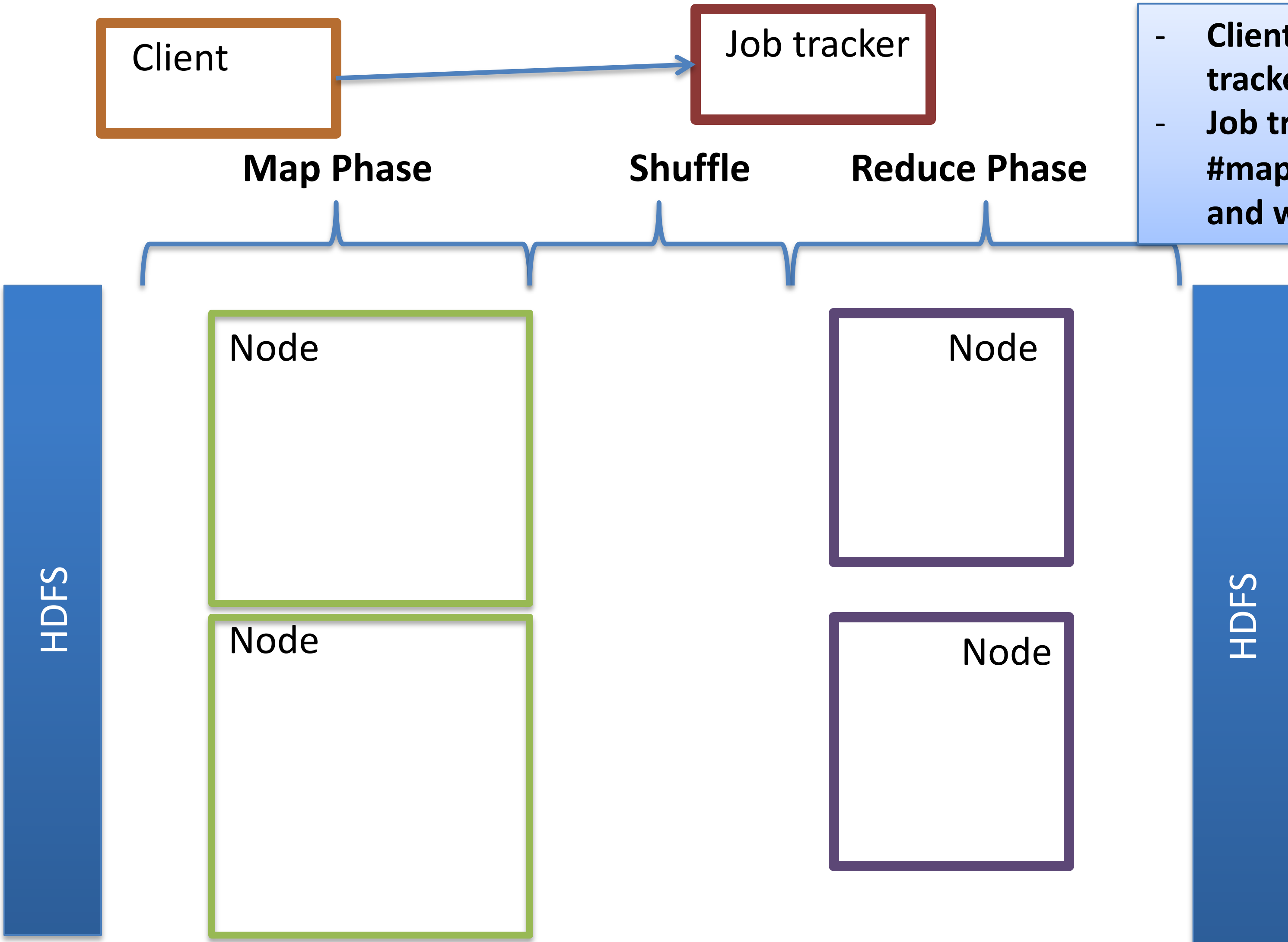
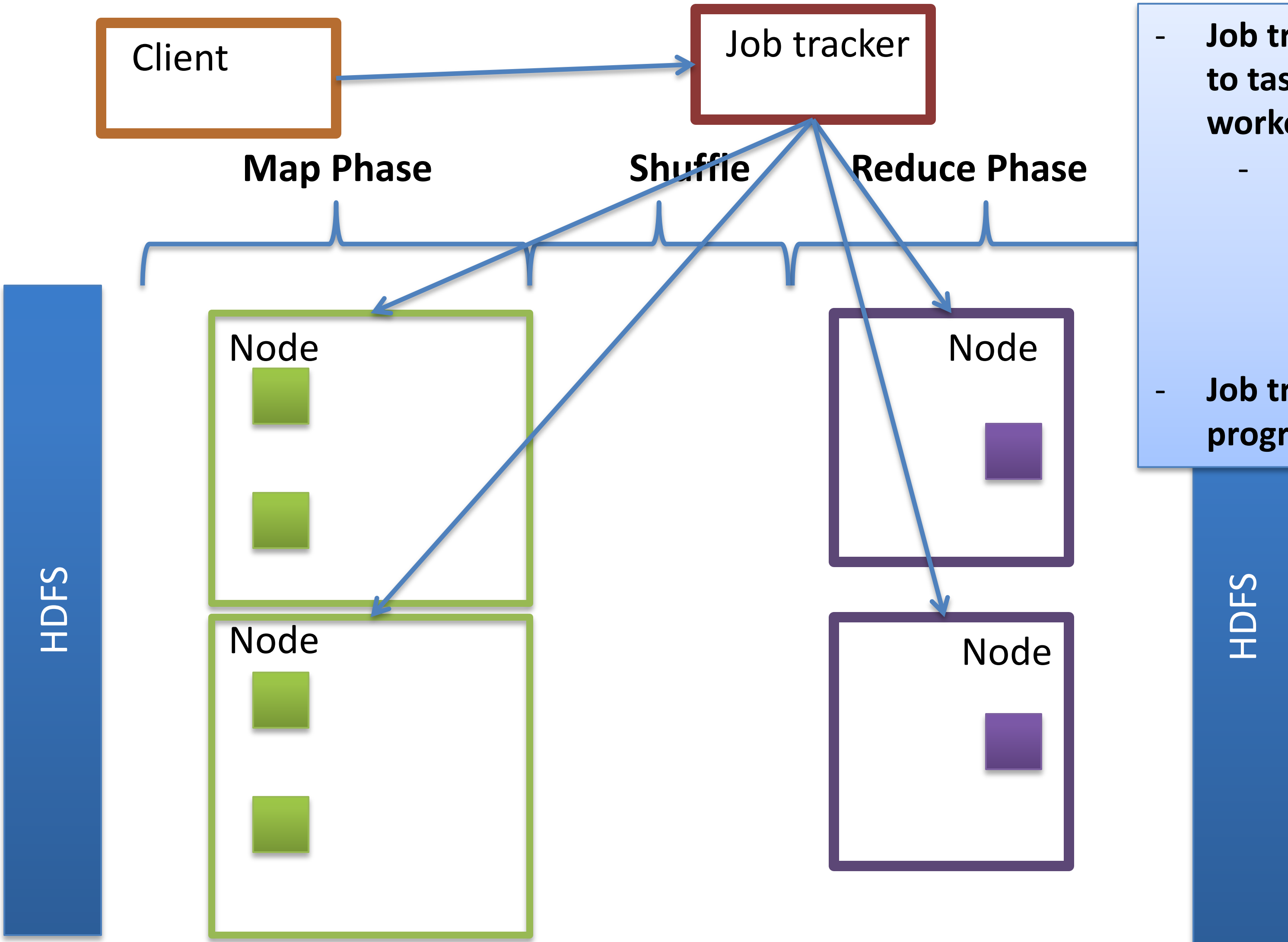
- Clients sends job to job tracker
- Job tracker decides #mappers, #reducers and which nodes to use

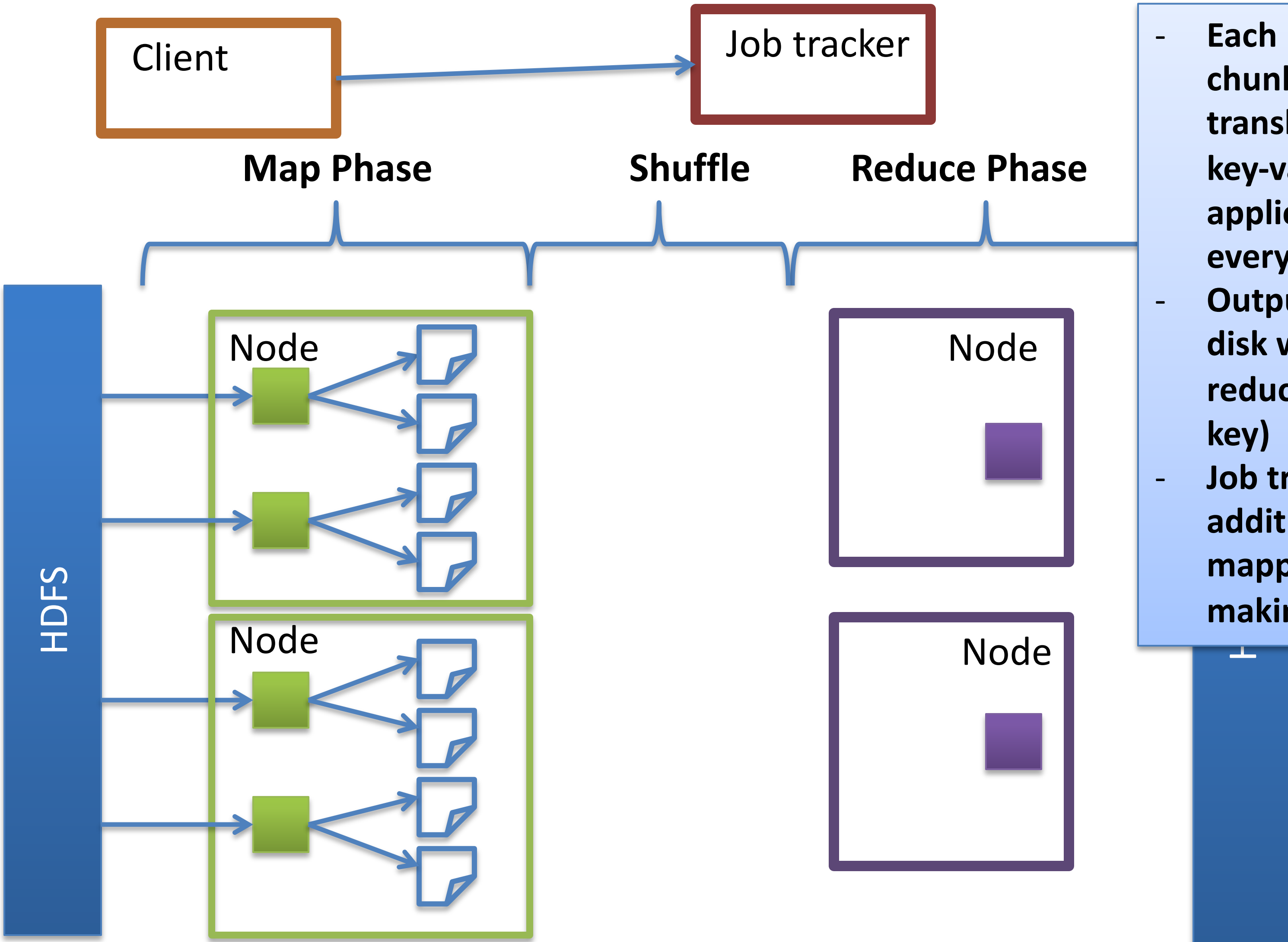


3. Hadoop – MR Job



- Job tracker sends jobs to task tracker on worker nodes
  - Try to schedule map jobs on nodes that store the chunk processed by a job
- Job tracker monitors progress

3. Hadoop – MR Job



- Each mapper reads its chunk from HDFS, translates the input into key-value pairs and applies the map UDF to every (k,v)
- Outputs are written to disk with one file per reducer (hashing on key)
- Job tracker may spawn additional mappers if mappers are not making progress

3. Hadoop – MR Job

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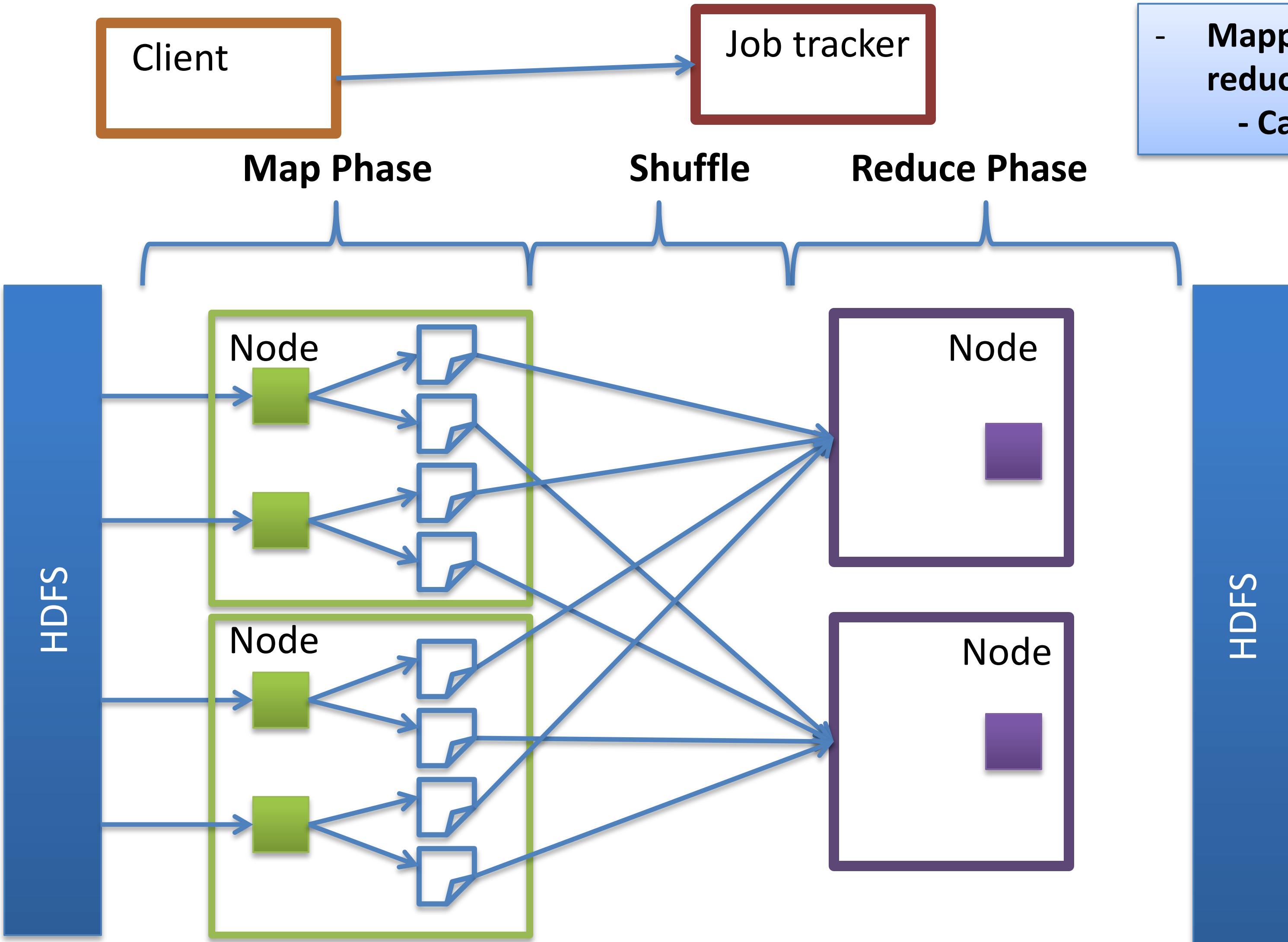
- Mappers send files to reducers (scp)
  - Called shuffle



3. Hadoop – MR Job

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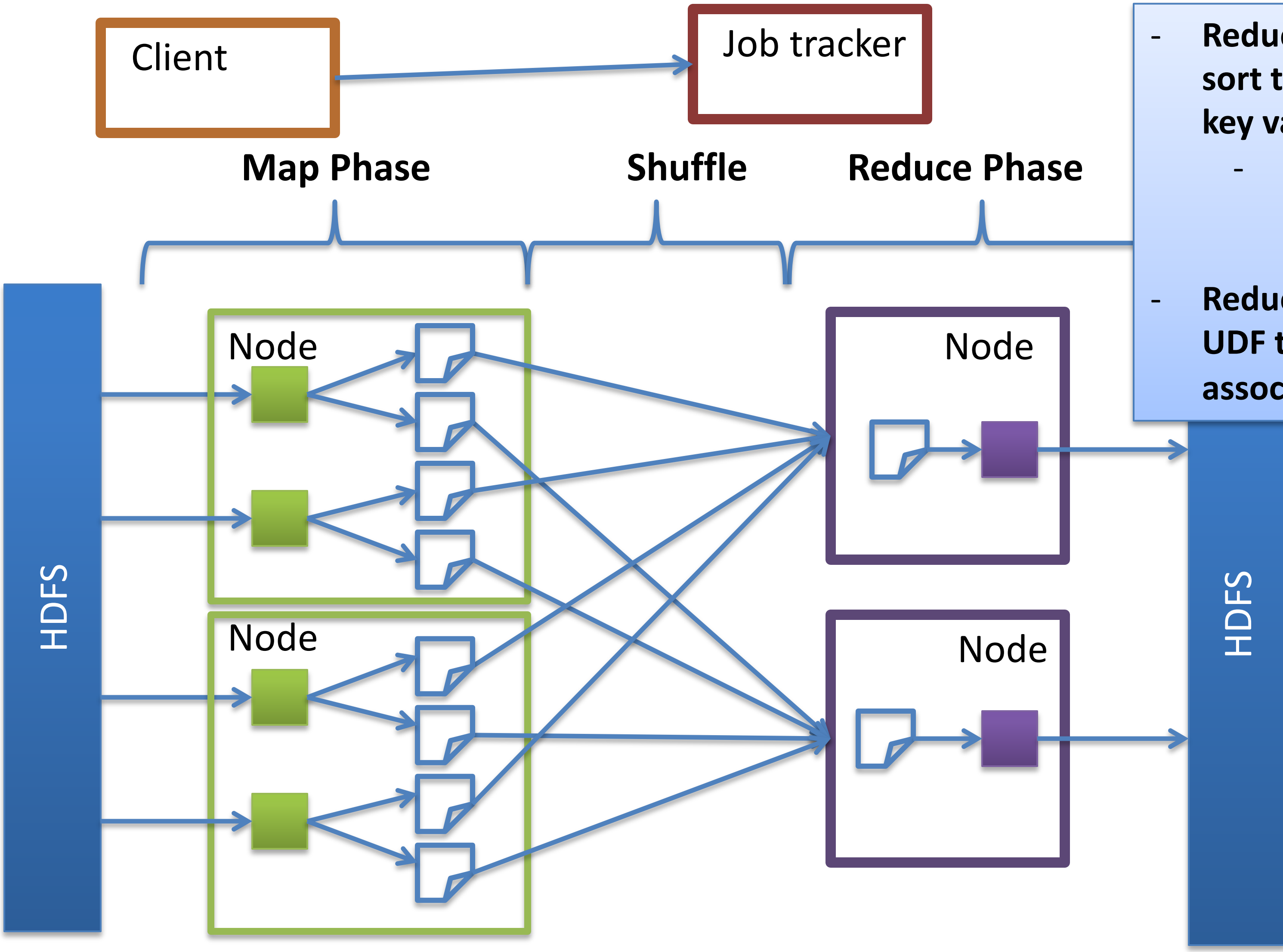

- Reducers merge and sort these input files on key values
  - External merge sort where runs already exists
- Reducer applies reduce UDF to each key and associated list of values

3. Combiners

- Certain reduce functions lend themselves to pre-aggregation
  - E.g., SUM(revenue) group by state
    - Can compute partial sums over incomplete groups and then sum up the pre-aggregated results
  - This can be done at the mappers to reduce amount of data send to the reducers
- Supported in Hadoop through a user provided combiner function
  - The combiner function is applied before writing the mapper results to local disk

3. Example code – Word count

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- https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html

```
public static class Map extends MapReduceBase implements Mapper<LongWritable, Text, Text, IntWritable> {
        private final static IntWritable one = new IntWritable(1);
        private Text word = new Text();

        public void map(LongWritable key, Text value, OutputCollector<Text, IntWritable> output, Reporter
reporter) throws IOException {
          String line = value.toString();
          StringTokenizer tokenizer = new StringTokenizer(line);
          while (tokenizer.hasMoreTokens()) {
            word.set(tokenizer.nextToken());
            output.collect(word, one);
          }
        }
}
```

3. Example code – Word count

- https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html

```
public static class Reduce extends MapReduceBase implements Reducer<Text, IntWritable, Text, IntWritable> {
         public void reduce(Text key, Iterator<IntWritable> values, OutputCollector<Text, IntWritable> outp
ut, Reporter reporter) throws IOException {
           int sum = 0;
           while (values.hasNext()) {
             sum += values.next().get();
           }
           output.collect(key, new IntWritable(sum));
         }
}
```

3. Example code – Word count

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```
public static void main(String[] args) throws Exception {
        JobConf conf = new JobConf(WordCount.class);
        conf.setJobName("wordcount");

        conf.setOutputKeyClass(Text.class);
        conf.setOutputValueClass(IntWritable.class);

        conf.setMapperClass(Map.class);
        conf.setCombinerClass(Reduce.class);
        conf.setReducerClass(Reduce.class);

        conf.setInputFormat(TextInputFormat.class);
        conf.setOutputFormat(TextOutputFormat.class);

        FileInputFormat.setInputPaths(conf, new Path(args[0]));
        FileOutputFormat.setOutputPath(conf, new Path(args[1]));

        JobClient.runJob(conf);
}
```

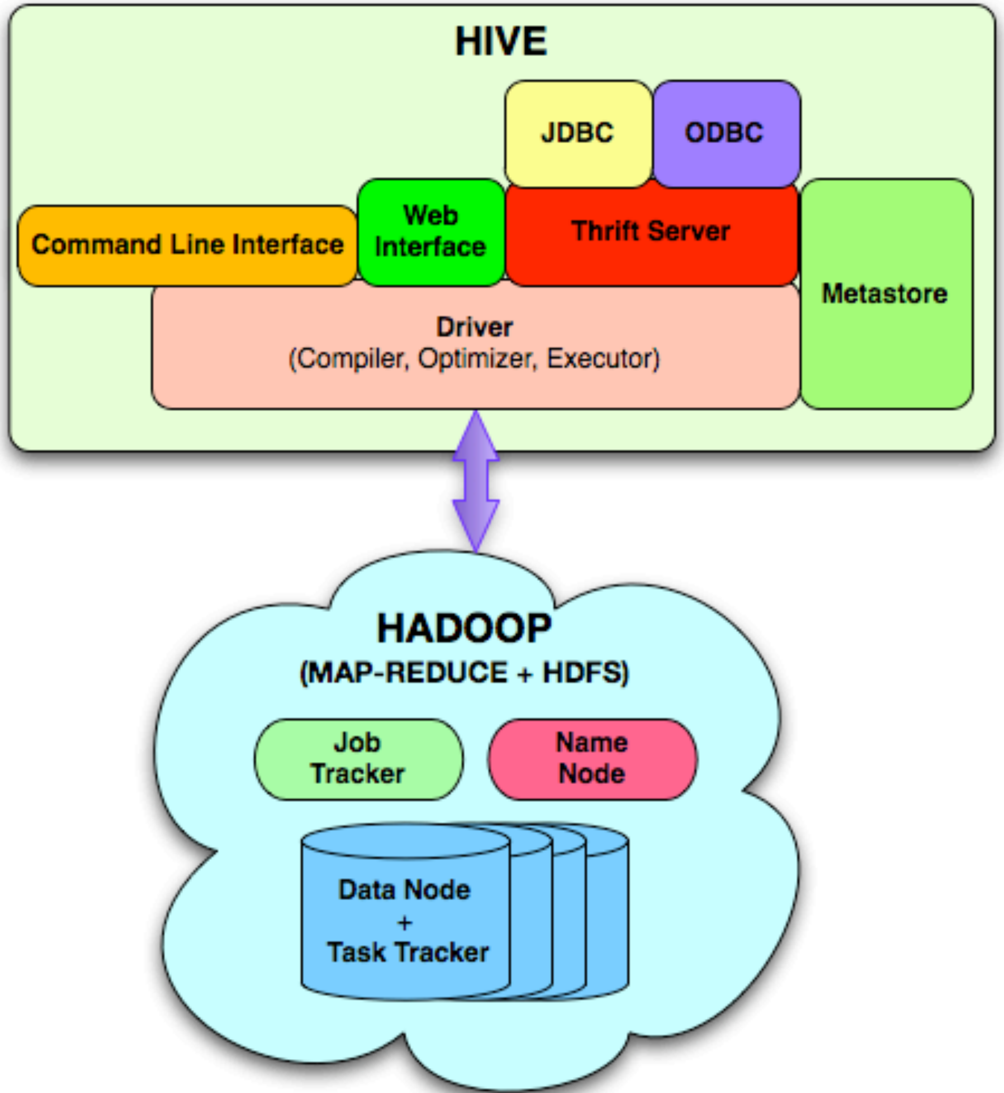
3. Systems/Languages on top of MapReduce

- Pig
  - Scripting language, compiled into MR
  - Akin to nested relational algebra
- Hive
  - SQL interface for warehousing
  - Compiled into MR
- …

- **Hive**
  - HiveQL: SQL dialect with support for directly applying given Map+Reduce functions as part of a query
  - HiveQL is compiled into MR jobs
  - Executed of Hadoop cluster

```
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';
```

3. Hive Architecture



3. Hive Datamodel

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- **Tables**
  - Attribute-DataType pairs
  - User can instruct Hive to partition the table in a certain way
- **Datatypes**
  - Primitive: integer, float, string
  - Complex types
    - Map: Key->Value
    - List
    - Struct
  - Complex types can be nested
- **Example**:

  CREATE TABLE t1(st string, fl float, li list<map<string, struct<p1:int, p2:int>>);
- **Implementation**:
  - Tables are stored in HDFS
  - Serializer/Deserializer - transform for querying

3. Hive - Query Processing

- Compile HiveQL query into DAG of map and reduce functions.
  - A single map/reduce may implement several traditional query operators
    - E.g., filtering out tuples that do not match a condition (selection) and filtering out certain columns (projection)
  - Hive tries to use the partition information to avoid reading partitions that are not needed to answer the query
    - For example
      - table **instructor**(name,department) is partitioned on department
      - **SELECT** name **FROM** instructor **WHERE** department = 'CS'
      - This query would only access the partition of the table for department 'CS'

3. Operator implementations

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- **Join implementations**
  - **Broadcast join**
    - Send the smaller table to all nodes
    - Process the other table partitioned
      - Each node finds all the join partners for a partition of the larger table and the whole smaller table
  - **Reduce join (partition join)**
    - Use a map job to create key-value pairs where the key is the join attributes
    - Reducer output joined rows

3. Example plan

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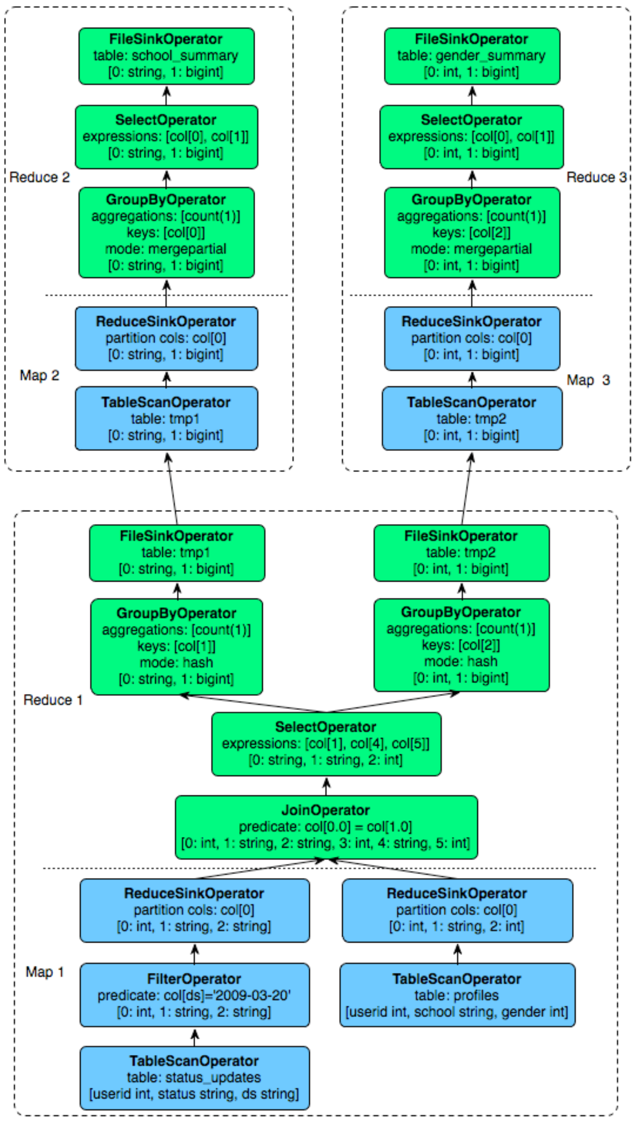

Spark

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- MR uses heavy materialization to achieve fault tolerance
  - A lot of I/O
- **Spark**
  - Works in main memory (where possible)
  - Inputs and final outputs stored in HDFS
  - Recomputes partial results instead of materializing them - **resilient distributed datasets** (*RDD*)
    - **Lineage**: Need to know from which chunk a chunk was derived from and by which computation

Summary

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- Big data storage systems
- Big data computation platforms
- Big data “databases”
- How to achieve scalability
  - Fault tolerance
  - Load balancing
- Big data integration
  - Pay-as-you-go
  - Schema later

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