Improving the MapReduce Big Data Processing Framework

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Contents

MapReduce Overview

Contributions

- MRPart: reducing data transfers in shuffle phase
- FP-Hadoop: making reduce phase more parallel
- hadoop_g5k: repeatable tests in Grid5000 platform

Conclusions

- Beyond MapReduce

MAPREDUCE OVERVIEW

MapReduce Overview

Programming model and framework

- Developed by Google for big data parallel processing in data centers
  - e.g., PageRank algorithm, inverted indexes
- Used in combination with other Google services (GFS, BigTable,…)
- Hadoop: an open-source implementation of MapReduce

Design requirements

- Executed on commodity clusters
- Failures are the norm rather than the exception

Goal

- Automatic parallelization and distribution and fault tolerance

Principle

- Data locality: move computation to data

Programming model

Data consists of key-value pairs (tuples)

Functions

- map: $(k_1,v_1) \rightarrow list(k_2,v_2)$
  - Processes input key-value pairs
  - For each input pair produces a set of intermediate pairs
- reduce: $(k_2,list(v_2)) \rightarrow list(k_3,v_3)$
  - Receives all the values for a given intermediate key
  - For each intermediate key produces a set of output pairs

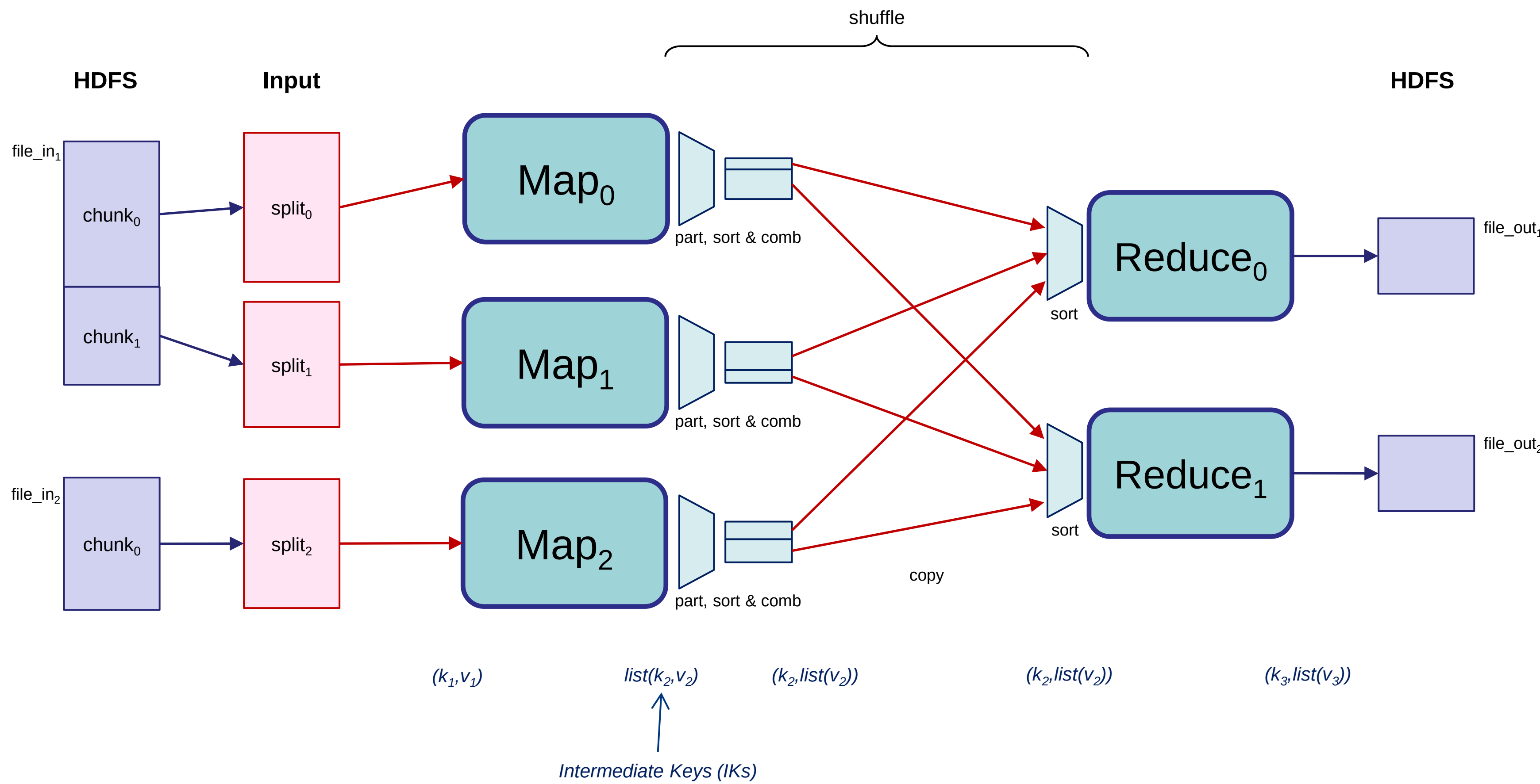
MapReduce Example

Wordcount: count the frequency of each word in a big file

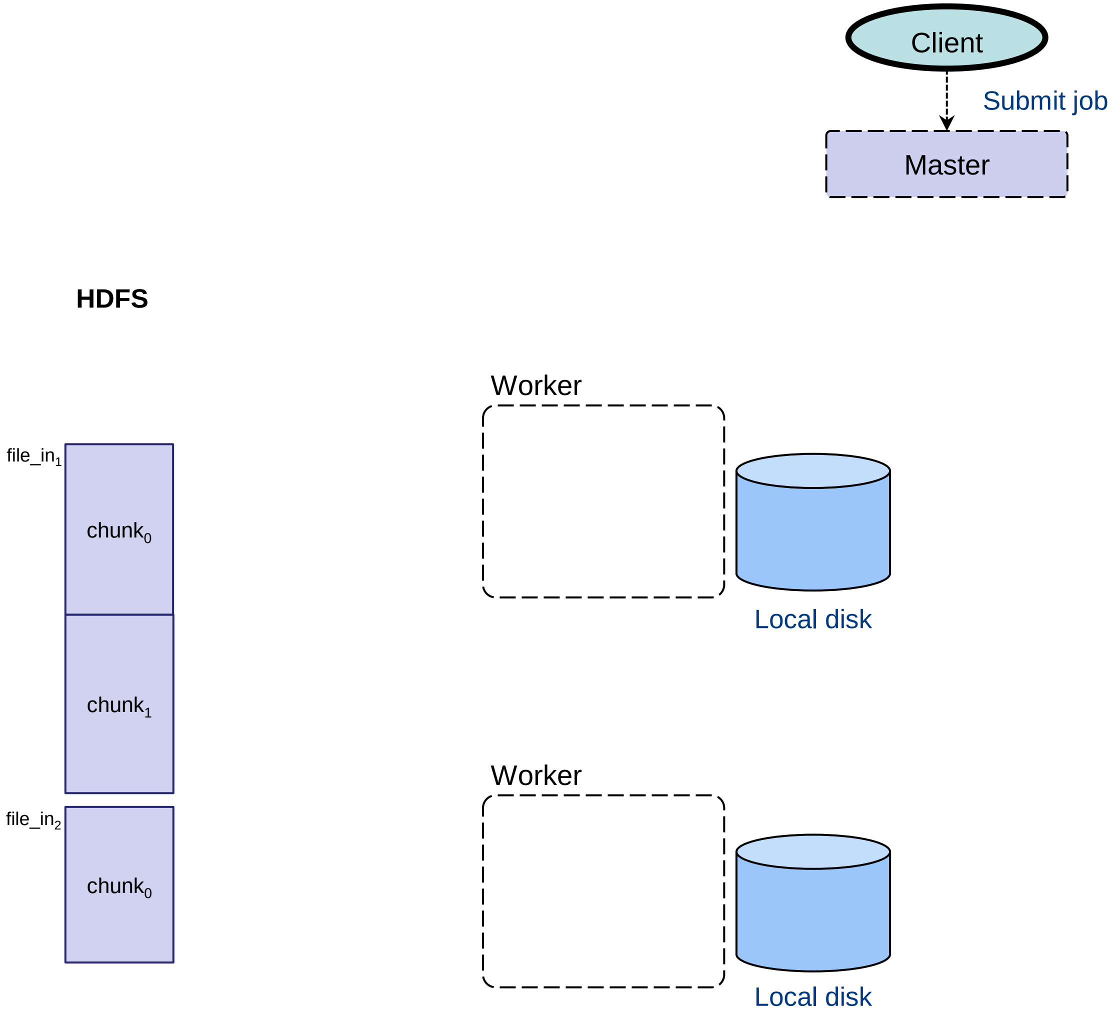
```
map(key, value)
// key: offset, value: a line
for each word w
  emit(w,1)

reduce(key, values)
// key: a word, values: list of counts
count = 0
for each v in values
  count += v
emit(key, count)
```

MapReduce Job Execution



Architectural view



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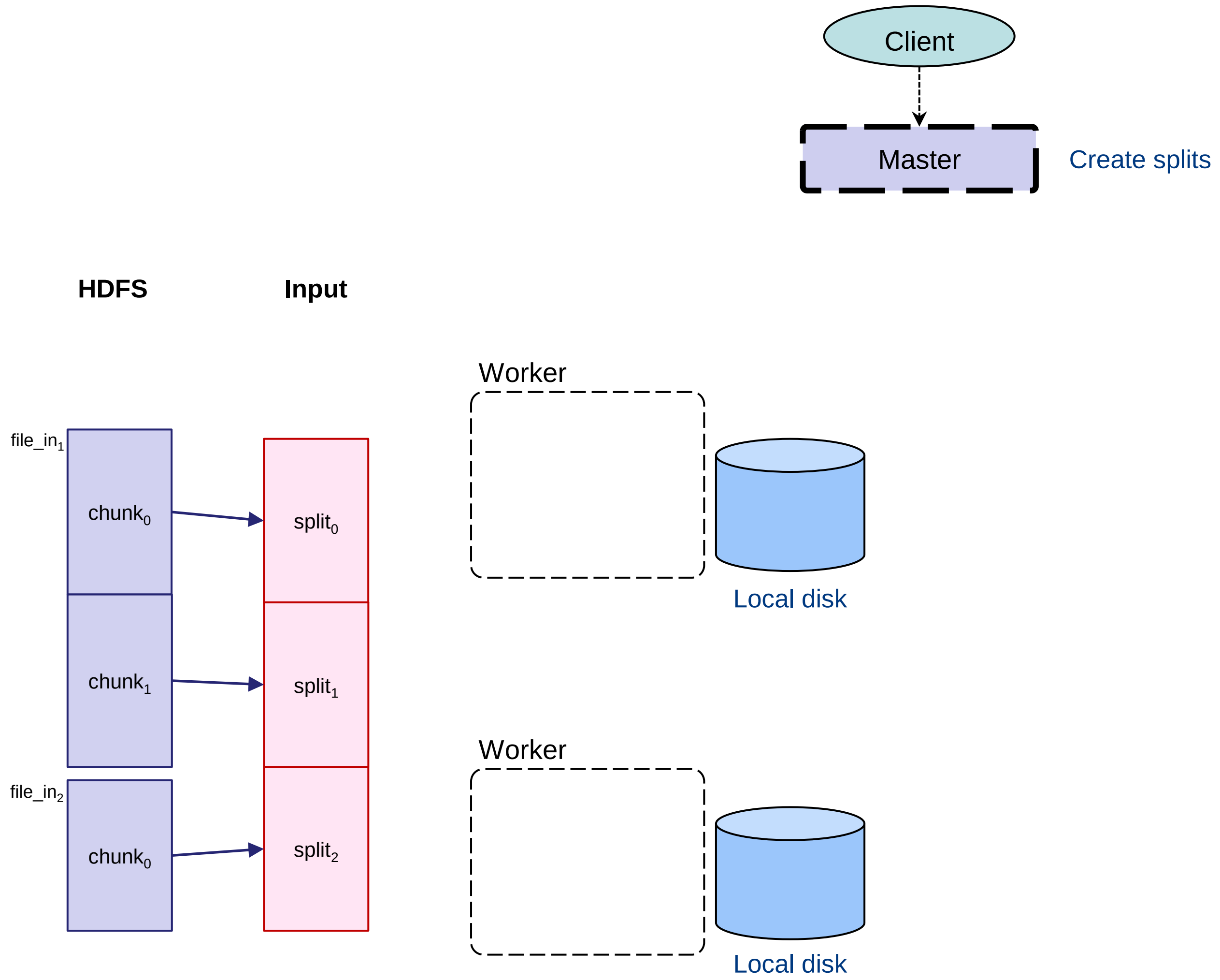

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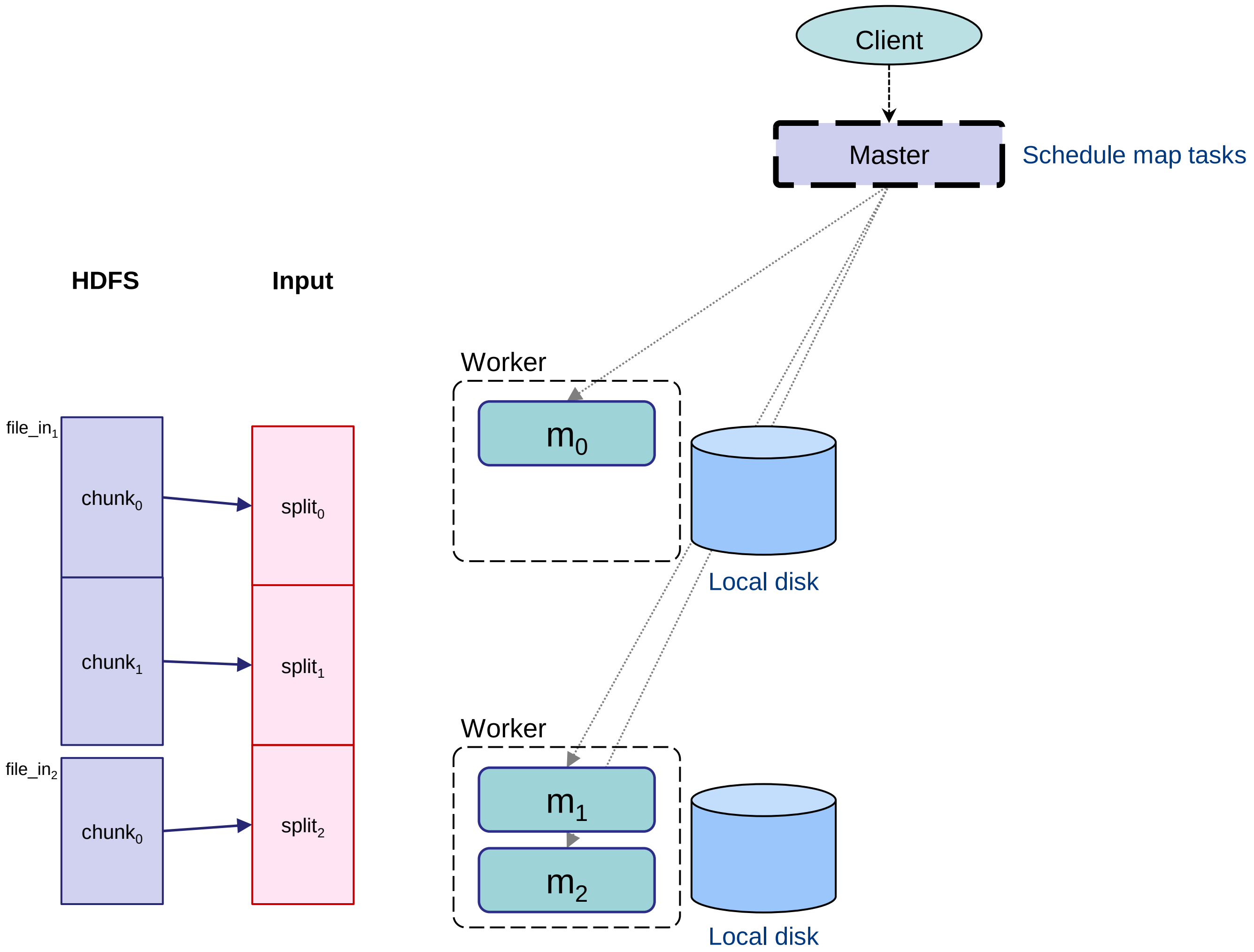

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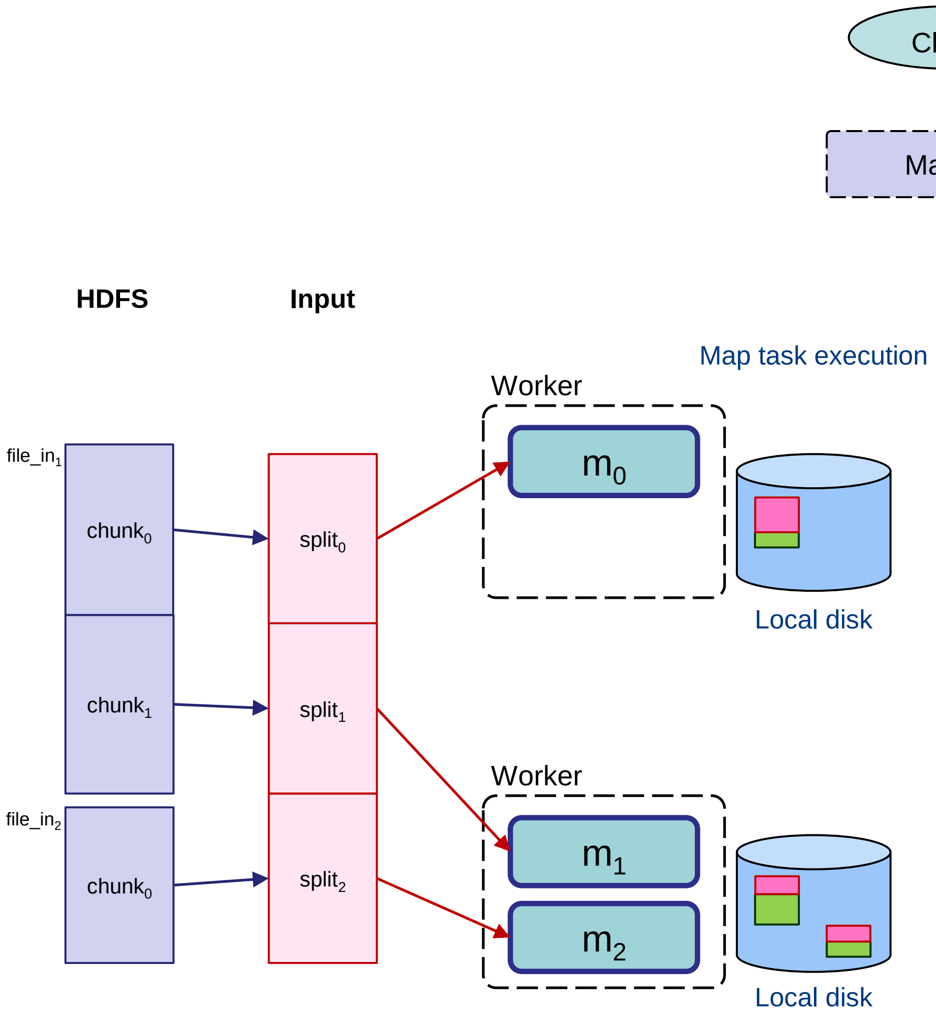

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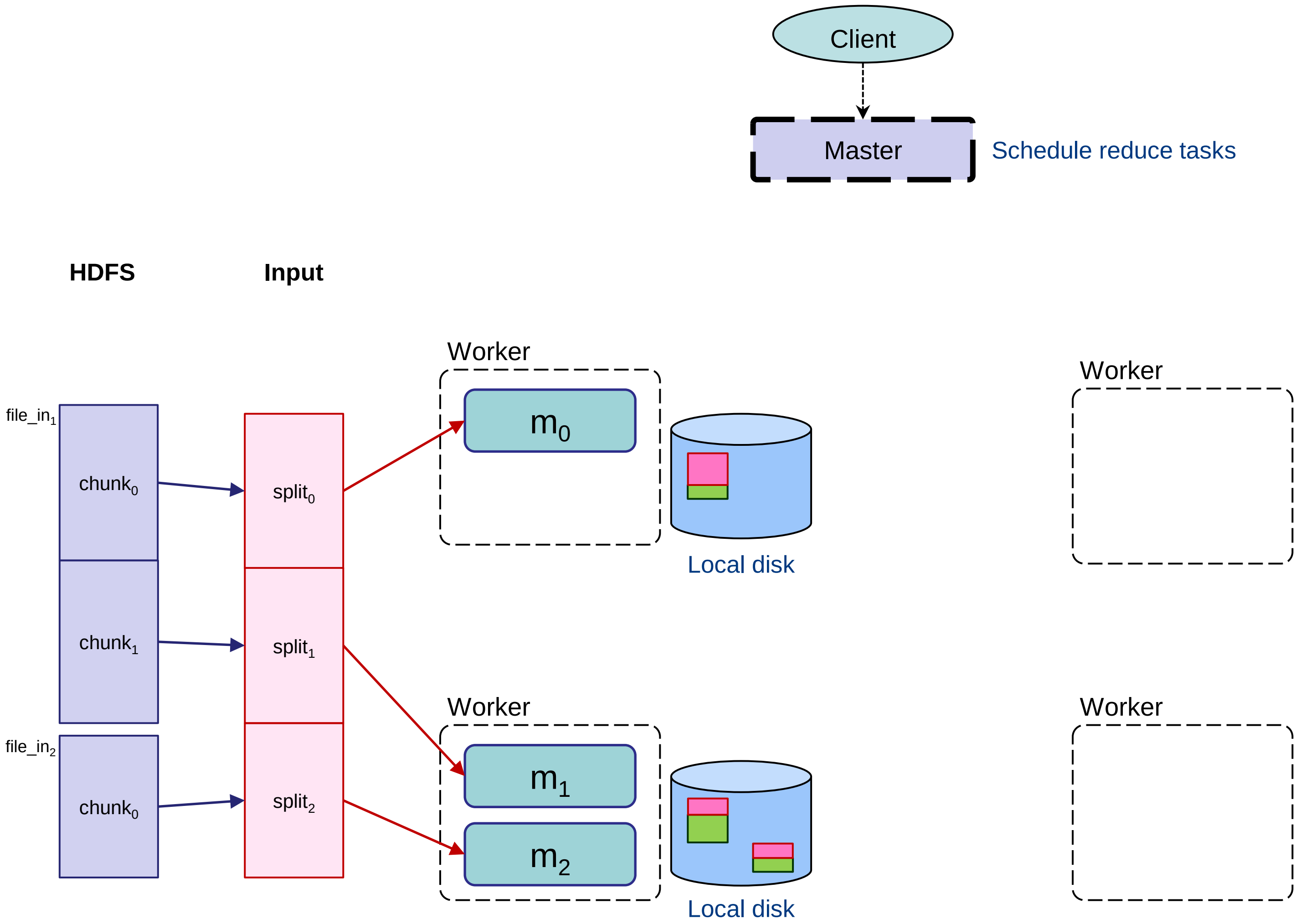

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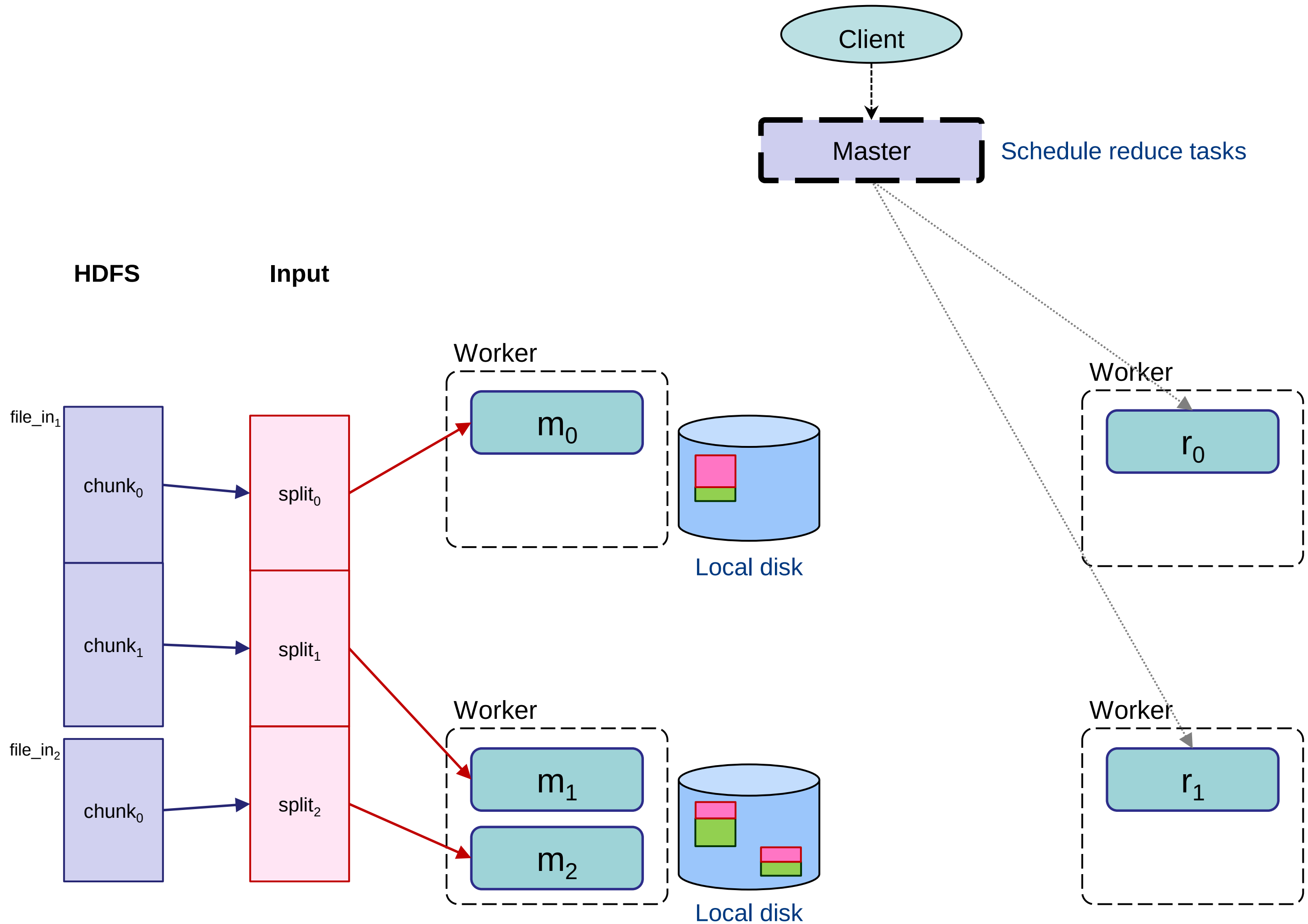

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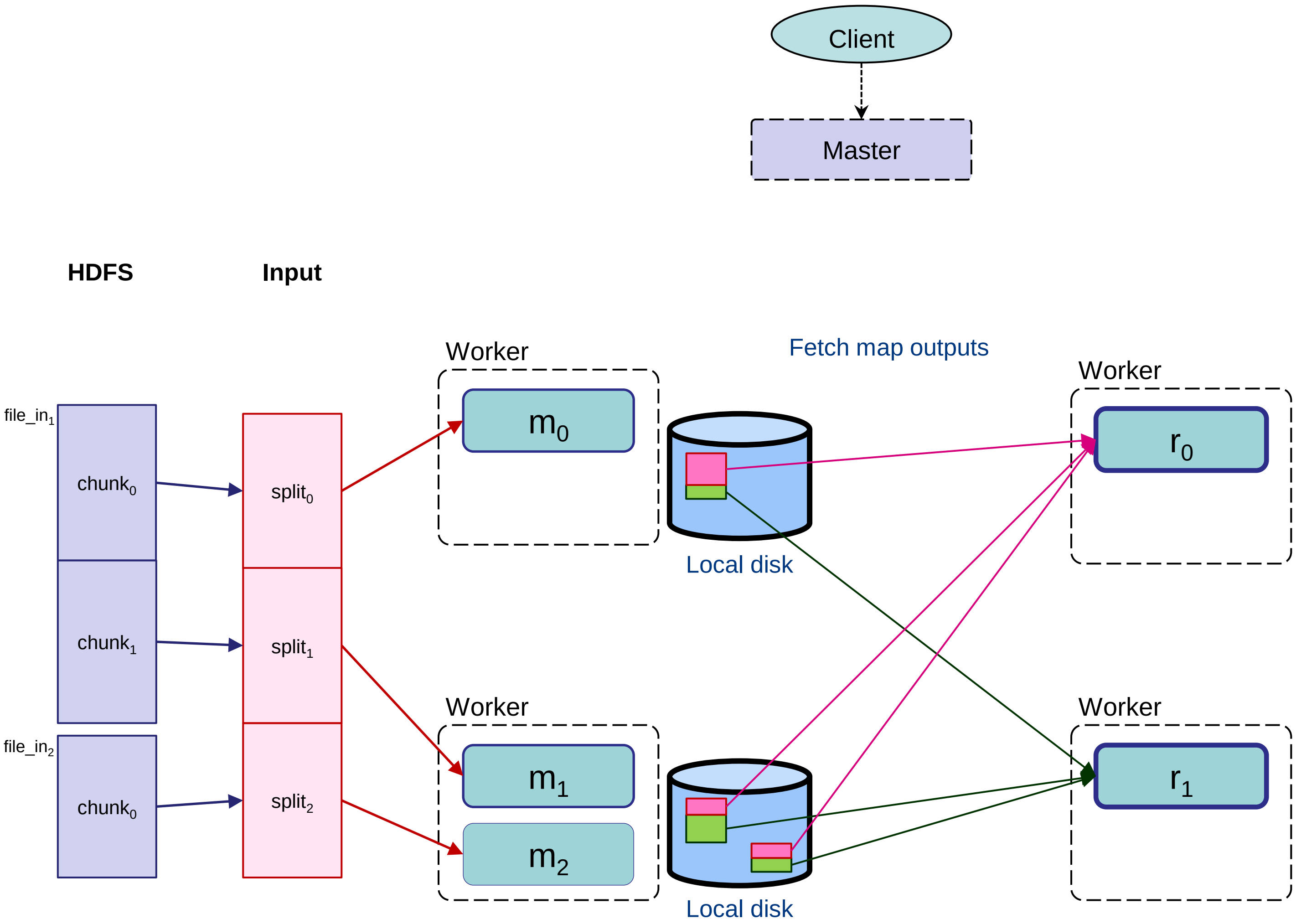
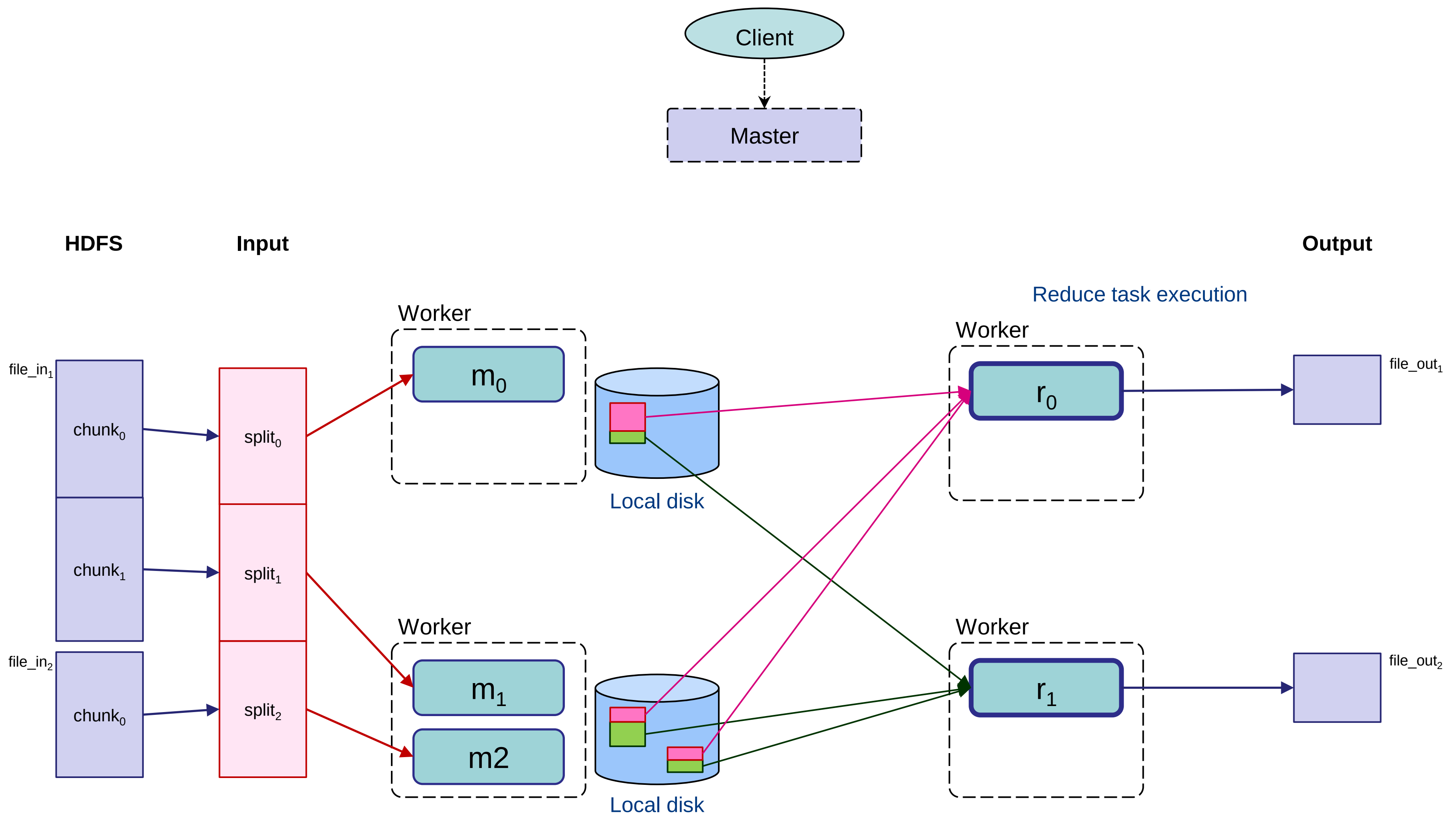


Architectural view

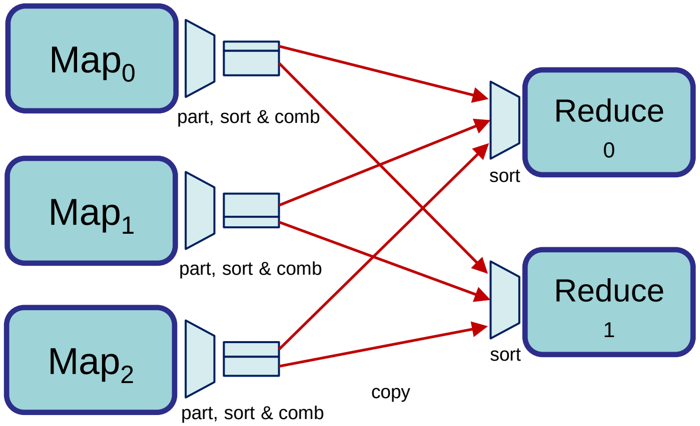


Shuffle Phase

Partitioning, sorting and transfer of data between map and reduce

Steps

- In the map task
  - Intermediate pairs are partitioned into R fragments
    - By default *part(key) = hash(key) mod* |*R*|
  - Pairs are sorted by key within each partition
- In the reduce task
  - Pairs with the same key are merged into a single (k_2, list(v_2)) pair and sent to the reduce function



Fault-Tolerance

Failures are the norm rather than the exception in large-scale data centers

Failure of workers

- Periodic heartbeat messages to the master
  - Finished map task and map and reduce tasks in progress are rescheduled

Failure of the master

- Periodic checkpoints to the DFS

Slow workers (stragglers)

- When all tasks are scheduled, running task are speculatively rescheduled in idle workers

OUR CONTRIBUTIONS

Overview

Shuffle overhead

- MRPart: minimizing data transfers between mappers and reducers

Skew prevention

- FP-Hadoop: parallelization of reduce phase with a multi-iteration intermediate phase

Experiment workflow

- hadoop_g5k: available tool for repeatable tests in Grid5000 platform

1. MR-Part: Improving Reduce Locality

Motivation

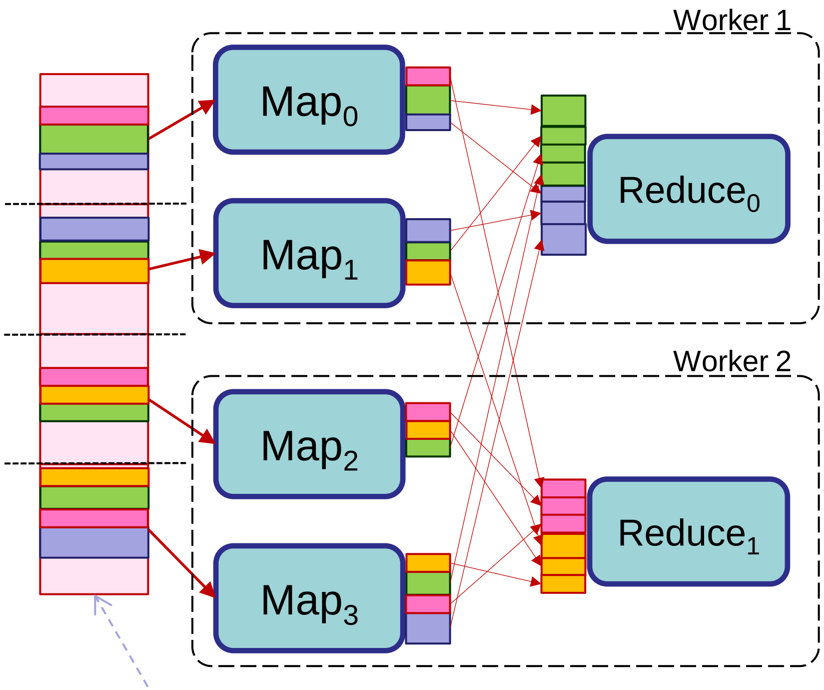
- The shuffle phase may involve big data transfers
- During shuffle, nodes are competing for bandwidth
- Result: some jobs are slowed down while this phase is completed

Ideal case

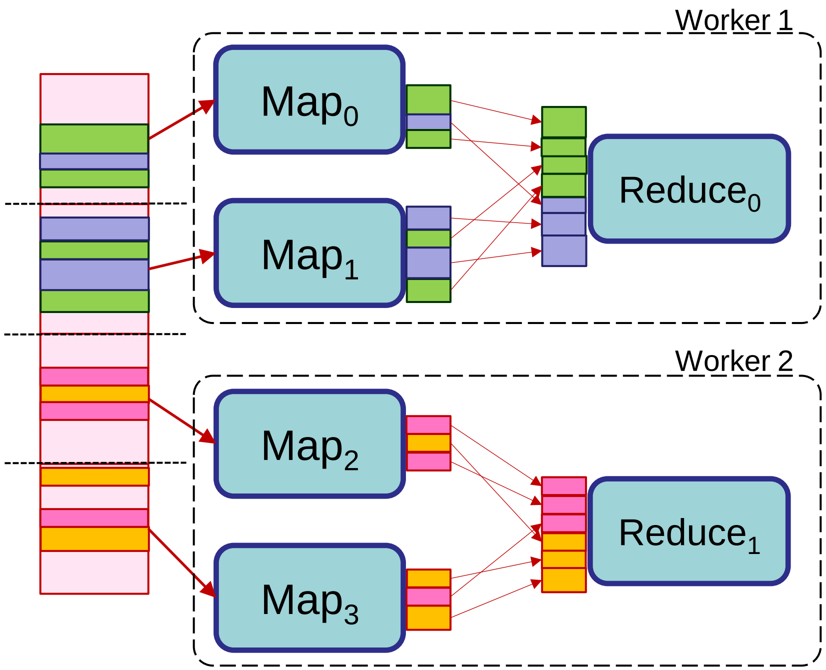
- No data transfer
  - All values for an intermediate key are produced in the same worker
  - They are assigned to a reduce task executed by the same worker

Motivation

Normal situation



Ideal case



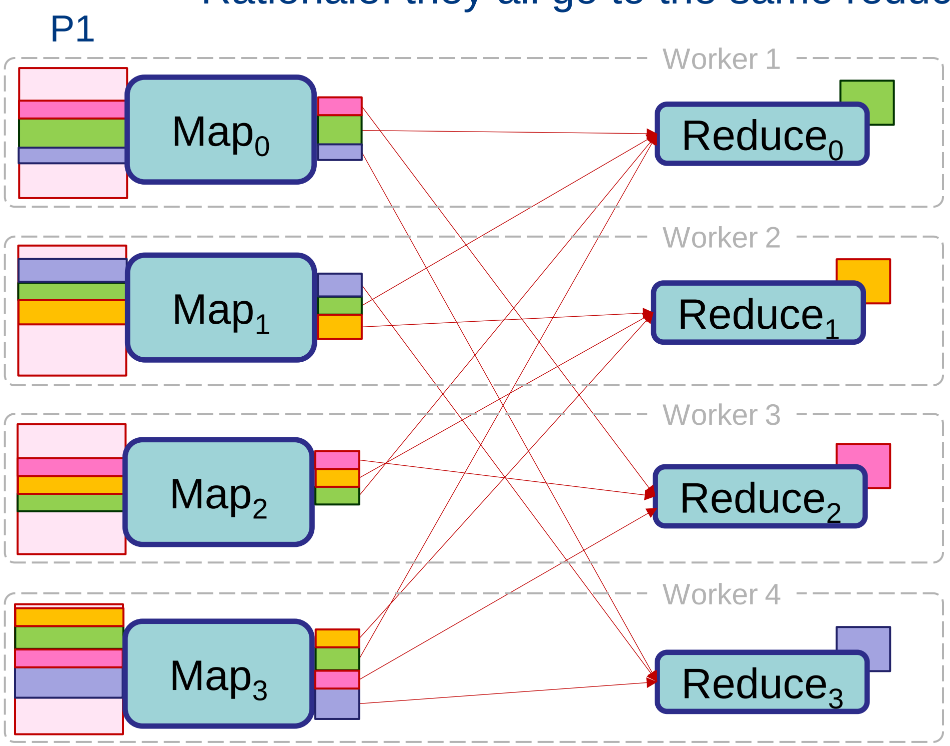
Colors represent tuples producing same IK (Intermediate Key)

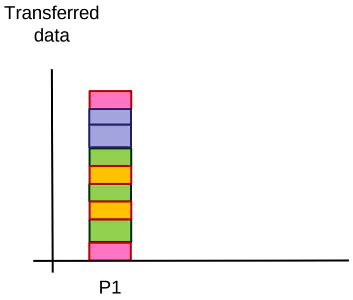
Main Idea of MR-Part

Given a file F and a set of MR jobs → Goal: minimize shuffle data transfer

Partitioning input data

- Tuples generating the same IK are placed together
- Rationale: they all go to the same reducer





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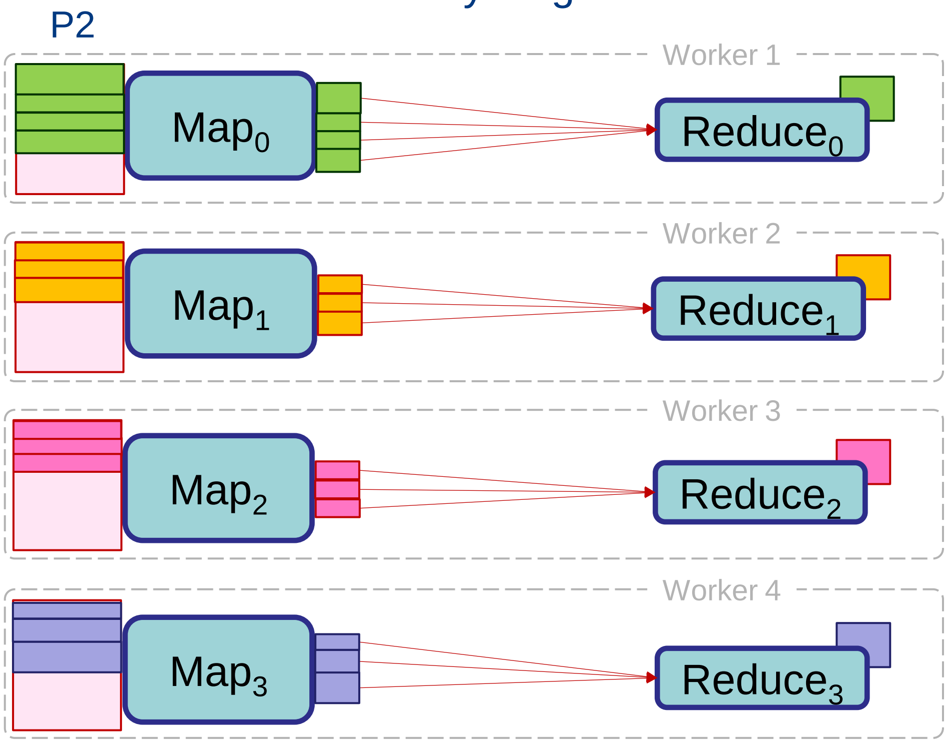
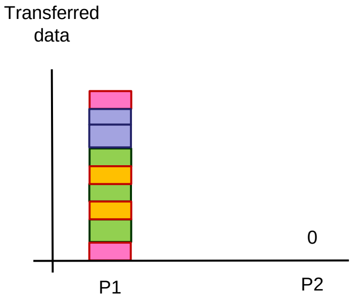
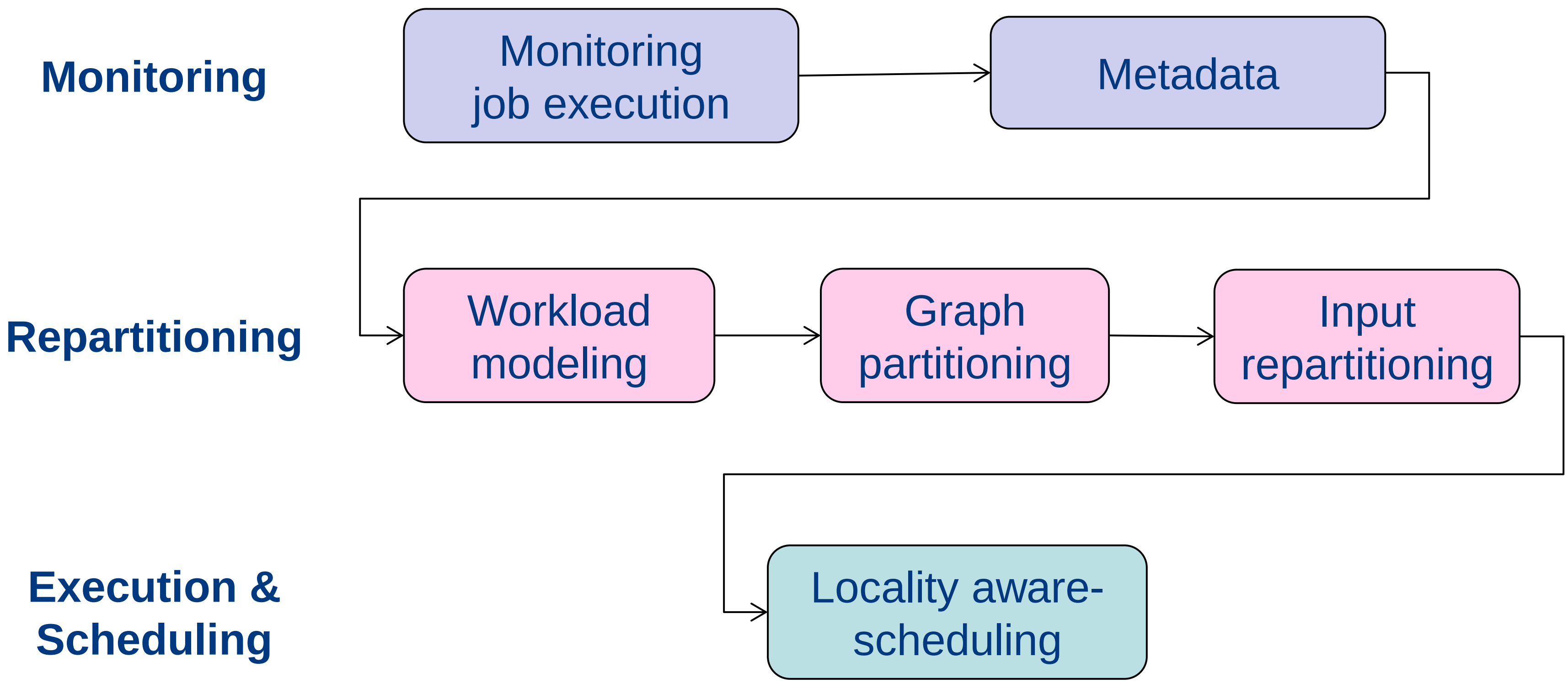




MR-Part Approach



Experiments

Environment

- **Grid5000**

Comparison

- Native Hadoop (NAT)
- Hadoop + reduce locality-aware scheduling (RLS)
- MR-Part (MRP)

Benchmark

- TPC-H, MapReduce version

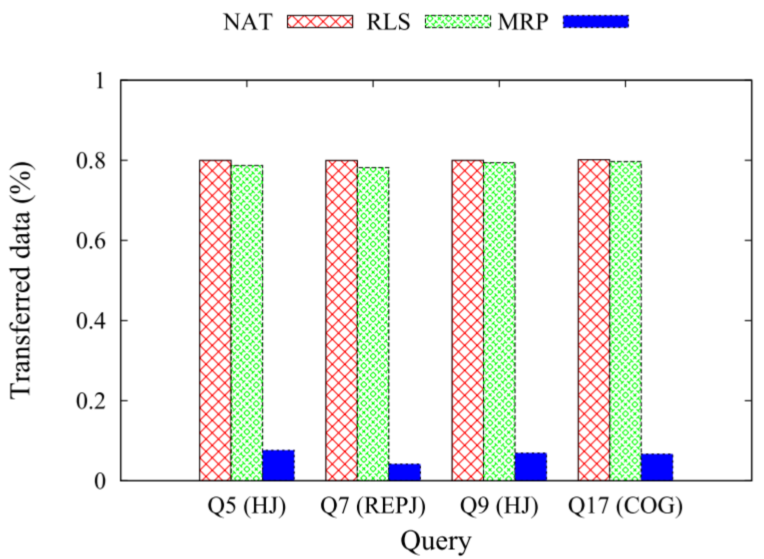
Parameters

- Data size, cluster size, bandwidth

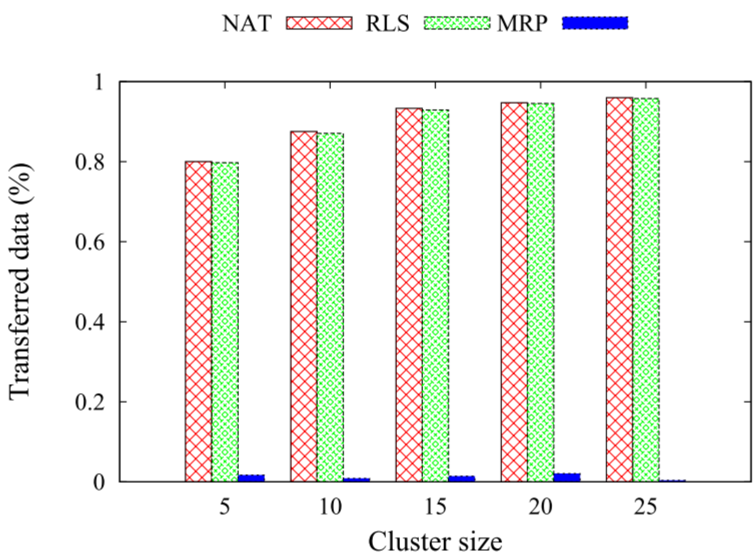
Metrics

- Transferred data
- Latency (response time)

Percentage of Transferred Data

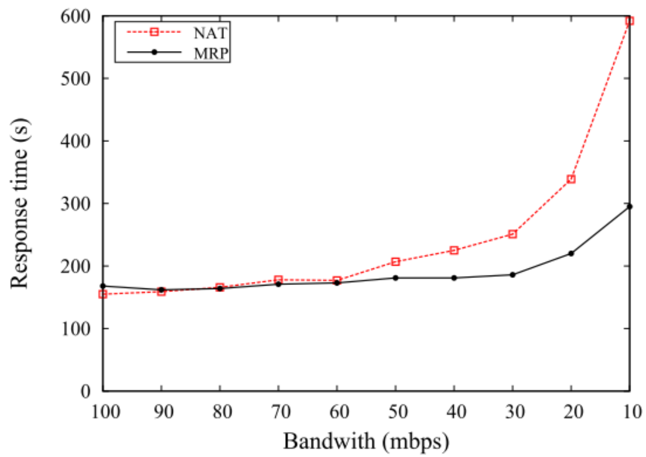


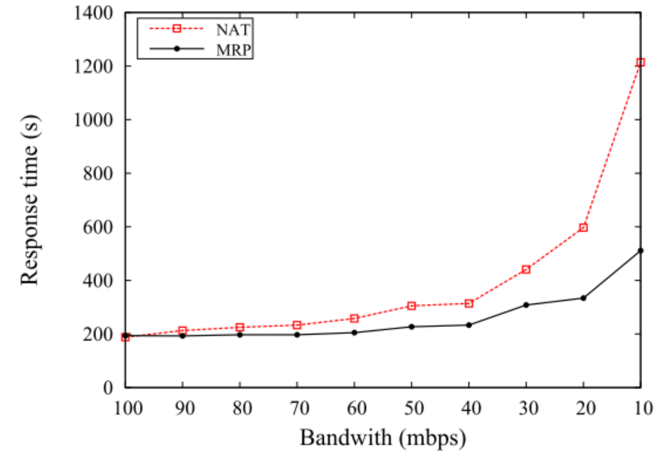
Different type of queries



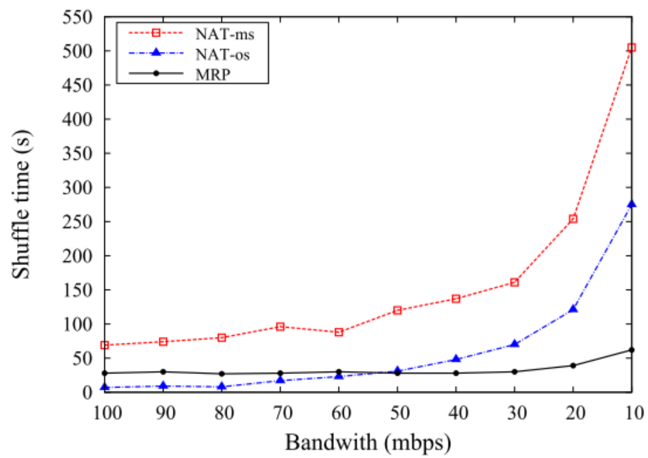
Varying cluster and data size

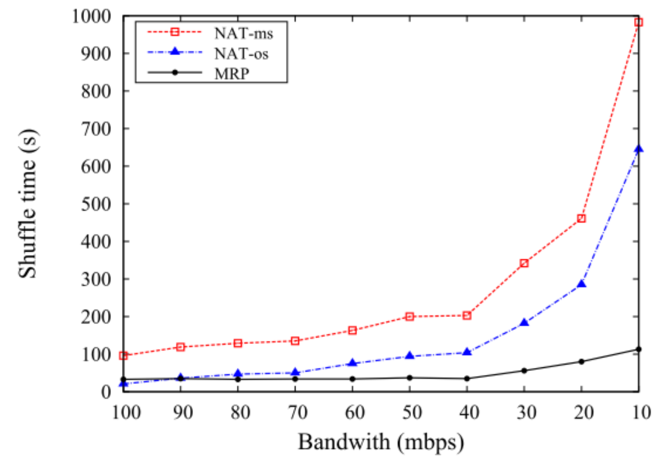
Varying bandwidth





Response time





Reduce time

TPC-H Q17

TPC-H Q9

2. FP-Hadoop: Making Reduce Phase More Parallel

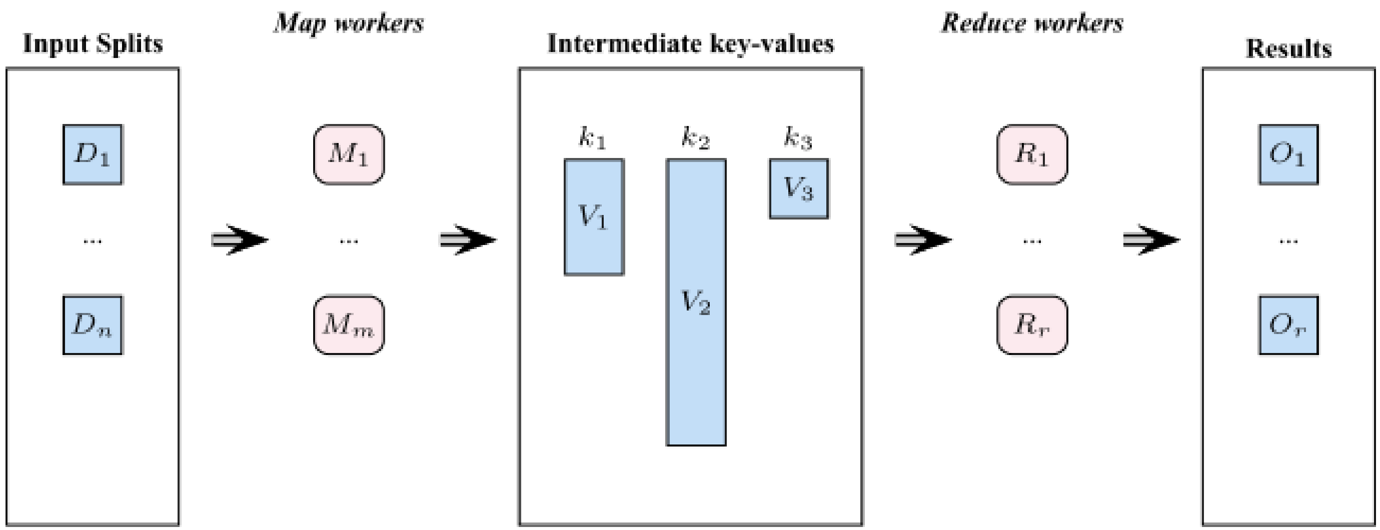
Parallelization in map phase

- Input data is divided into splits of similar size
- Map tasks are scheduled in free workers
  - Each map tasks consumes one of the splits

Parallelization in the reduce phase

- Intermediate keys are assigned to reduce task depending on a function
- Size of reduce tasks cannot be defined a priori
  - Even with ideal partitioning function, keys with a lot of values still produce overloaded splits

2. FP-Hadoop: Making Reduce Phase More Parallel



Main Idea of FP-Hadoop

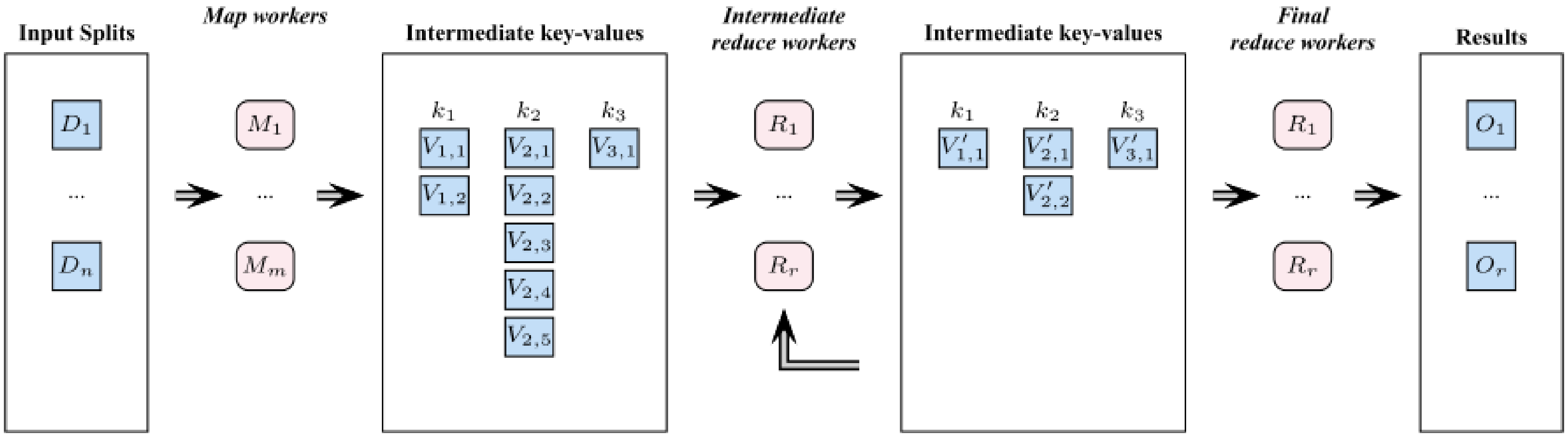
Reduce input data is divided into splits (IR splits)

- The size of the splits is bounded
- Splits are consumed in the same way as in the map phase

Reduce function is divided into two functions

- Intermediate reduce: parts that can be done in parallel
  - Eventually it can be executed in multiple phases
- Final reduce: performs the final grouping

Main Idea of FP-Hadoop



FP-Hadoop approach

A modified scheduler is injected into MR framework

- The scheduler selects a subset of values of each key and creates an IR split
- IR split is assigned to an IR task and allocated in a worker
- This process can be repeated several times
- At the end, a final reducer regroups the values of each key

Experiments

Environment

- **Grid5000**

Comparison

- Native Hadoop (NAT)
- FP-Hadoop (FPH)

Benchmark

- Top-k query (sort, pagerank, inverted index)
- Synthetic data set, Wikipedia data

Parameters

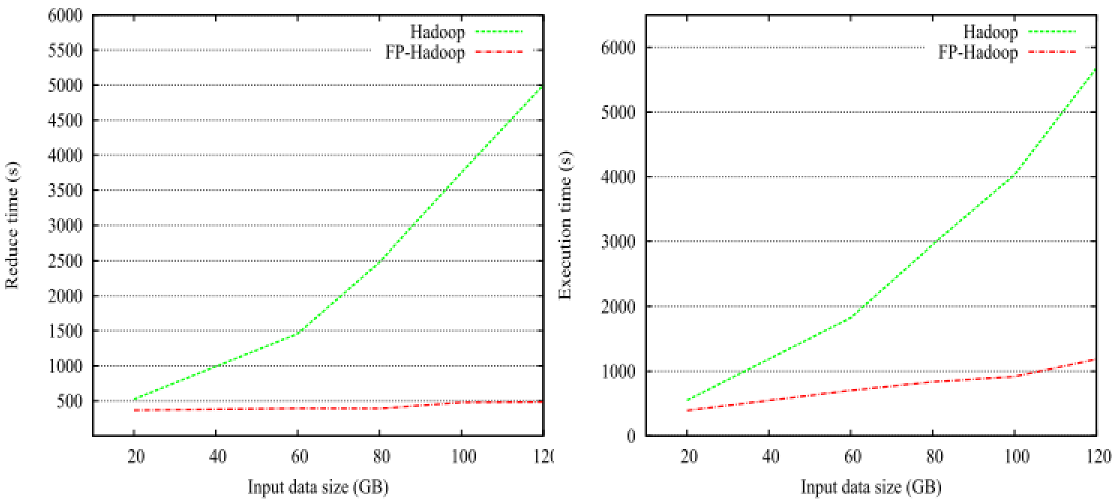
- Data size, cluster size, Skew, FPH conf parameters

Metrics

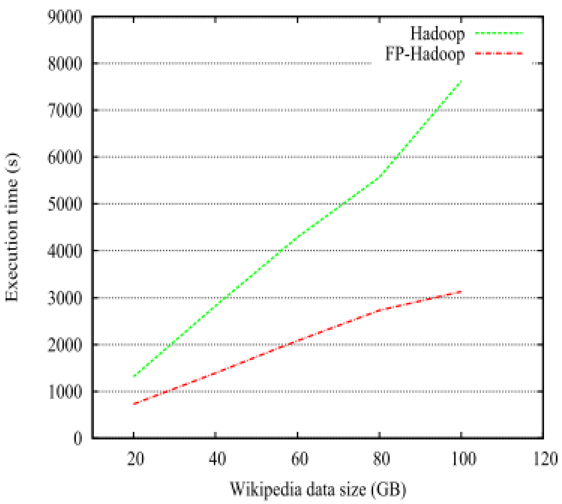
- Latency (response time)

Results

Comparison with native Hadoop



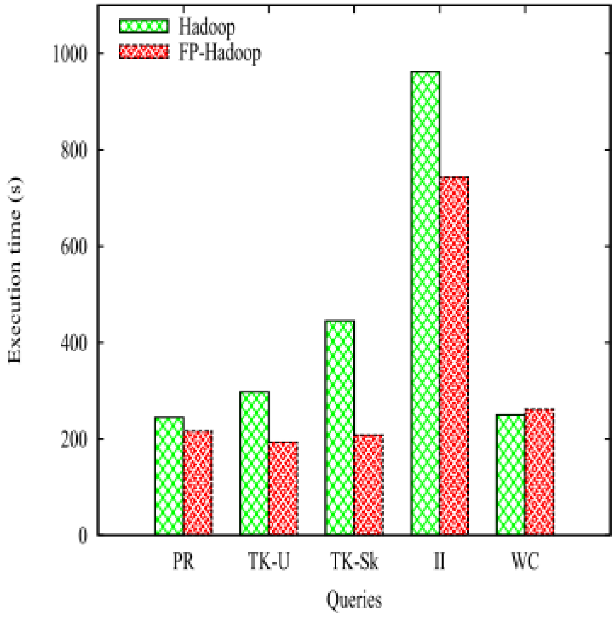
Synthetic dataset, top-k query



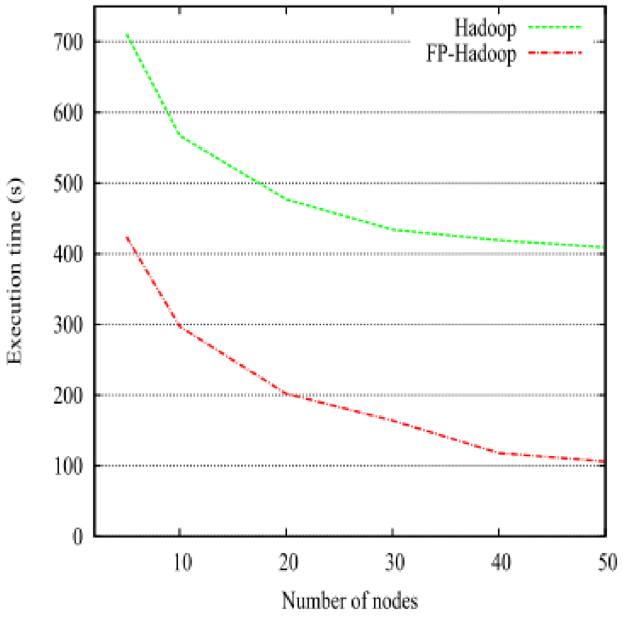
Wikipedia stats, top-k query

Results

Comparison with native Hadoop



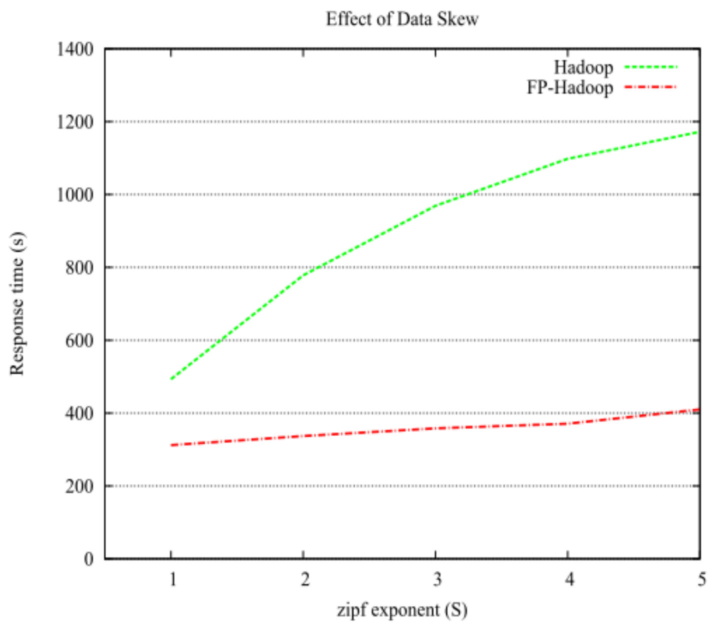
Different queries



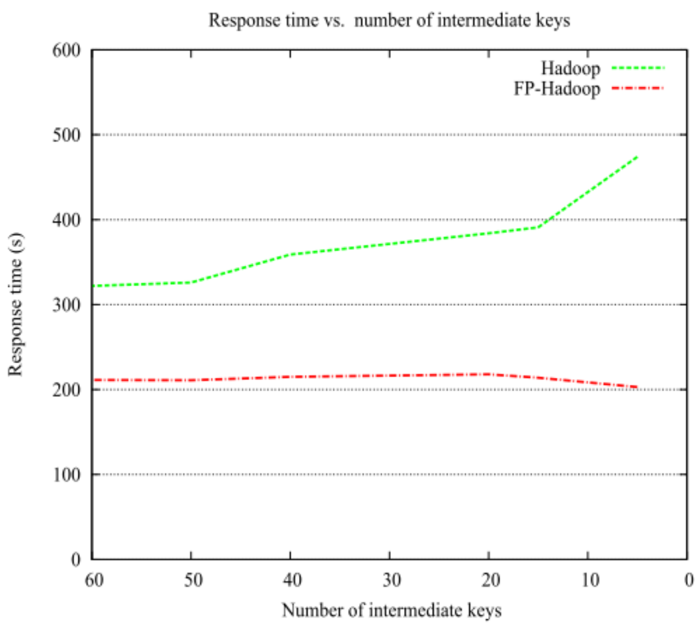
Cluster size

Results

Comparison with native Hadoop



Skew (zipf exponent)



Number of keys

3. hadoop_g5k: Repeatable tests in Grid5000

Experimental evaluation in Grid5000 platform

- French grid infrastructure deployed over 11 sites
- Aims to provide “highly reconfigurable, controllable and monitorable experimental platform to its users”

Hadoop_g5k

- A tool to facilitate repeatable tests with Hadoop in the Grid500 platform
- Publicly available

https://github.com/mliroz/hadoop_g5k

CONCLUSION

Summary

Overview of MapReduce

Contributions

- Proposed prototypes:
  - MR-Part: reducing data transfer in shuffle phase
  - FP-Hadoop: making reduce phase more parallel
- Hadoop_g5k: repeatable experiments in Grid5000

Beyond MapReduce

Great interest of industry in MapReduce

- Amazon Elastic MapReduce, MapR, Cloudera, Hortonworks, IBM BigInsights

Hadoop ecosystem

- HBase, Hive, Pig, YARN, Mahout, Oozie

Post-Hadoop frameworks

- Google Dremel
- Apache Spark

Thank you

Questions?