Data acquisition, extraction, and storage

Distributed Computing with MapReduce and Beyond

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ÉCOLE NORMALE SUPÉRIEURE | PSL

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Outline

Distributed Data Systems

- Distributed Data Management
- Distributed File Systems (GFS/HDFS)

MapReduce

Limitations of MapReduce

Alternative Distributed Computation Models

Distributed systems

A distributed system is an application that coordinates the actions of several computers to achieve a specific task.

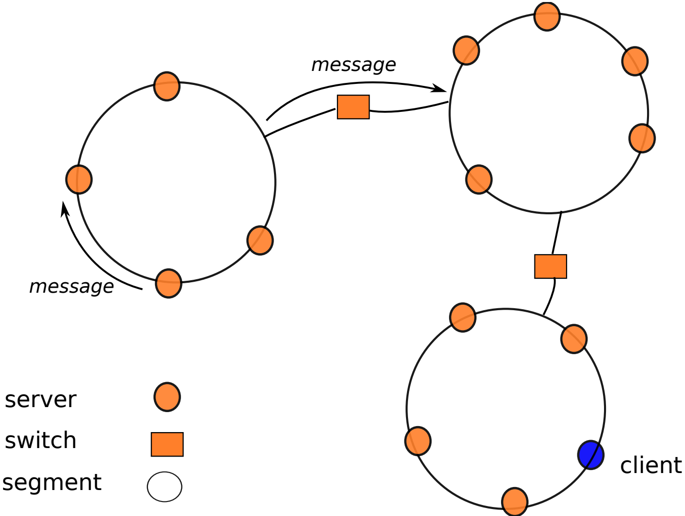
This coordination is achieved by exchanging messages which are pieces of data that convey some information.
⇒ "shared-nothing" architecture → no shared memory, no shared disk.

The system relies on a network that connects the computers and handles the routing of messages.
⇒ Local area networks (LAN), Peer to peer (P2P) networks...

Client (nodes) and Server (nodes) are communicating software components: we assimilate them with the machines they run on.

LAN-based infrastructure: clusters of machines

Three communication levels: “racks”, clusters, and groups of clusters.



Example: data centers

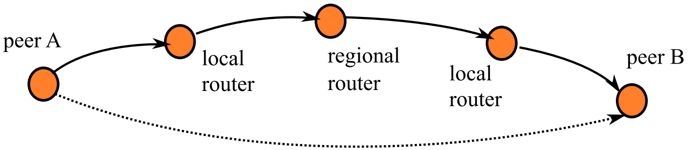
Typical setting of a Google data center.

1. $\approx$ 40 servers per rack;
2. $\approx$ 150 racks per data center (cluster);
3. $\approx$ 6,000 servers per data center;
4. how many clusters? Google's secret, and constantly evolving ...

Rough estimate: 150-200 data centers? 1,000,000 servers?

P2P infrastructure: Internet-based communication

Nodes, or "peers" communicate with messages sent over the Internet network.



The physical route may consist of 10 or more forwarding messages, or "hops".

Suggestion: use the `traceroute` utility to check the route between your laptop and a Web site of your choice.

Performance

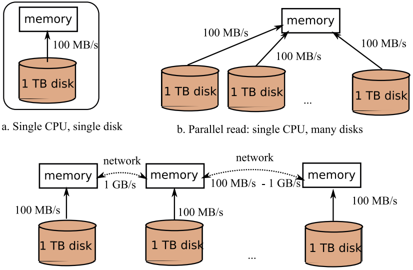
Type	Latency	Bandwidth
Disk	$\approx 5 \times 10^{-3}$ s	At best 200 MB/s
SSD	$\approx 10^{-4}$ s	200–500 MB/s
LAN	$\approx 10^{-3}$ s	100 Mb/s to 10Gb/s (single-rack)
Internet	10–100 ms (highly variable)	A few MB/s (highly variable)

Bottom line (1): it can be one order of magnitude faster to exchange main memory data between 2 machines in the same rack of a data center, than to read on the disk.

Bottom line (2): exchanging through the Internet is slow and unreliable with respect to LANs.

Distribution, why?

Sequential access. It takes a couple of hours to read a 1 TB disk.
Parallel access. With 100 disks, assuming that the disks work in parallel and sequentially: about 1 minute.
Distributed access. With 100 computers, each disposing of its own local disk: each CPU processes its own dataset.



a. Single CPU, single disk
b. Parallel read: single CPU, many disks
c. Distributed reads: an extendible set of servers

The latter solution is scalable, by adding new computing resources.

Performance of data-centric distr. systems

1. disk transfer rate is a bottleneck for large scale data management; parallelization and distribution of the data on many machines is a means to eliminate this bottleneck;
2. *write once, read many*: a distributed storage system is appropriate for large files that are written once and then repeatedly scanned;
3. *data locality*: bandwidth is a scarce resource, and program should be "pushed" near the data they must access to.

A distr. system also gives an opportunity to reinforce the security of data with replication.

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History and development of GFS

Google File System, a paper published in 2003 by Google Labs at OSDI.

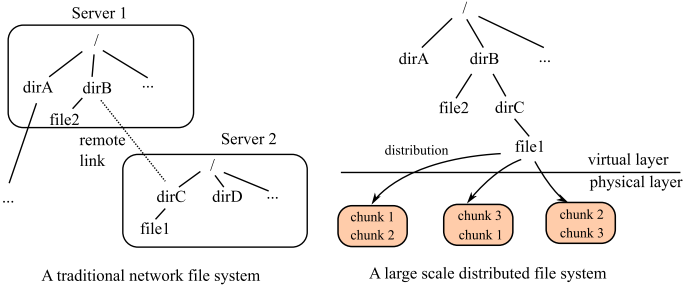
Explains the design and architecture of a distributed system apt at serving very large data files; internally used by Google for storing documents collected from the Web.

Open Source versions have been developed at once: Hadoop File System (HDFS), and Kosmos File System (KFS).

The problem

Why do we need a distributed file system in the first place?

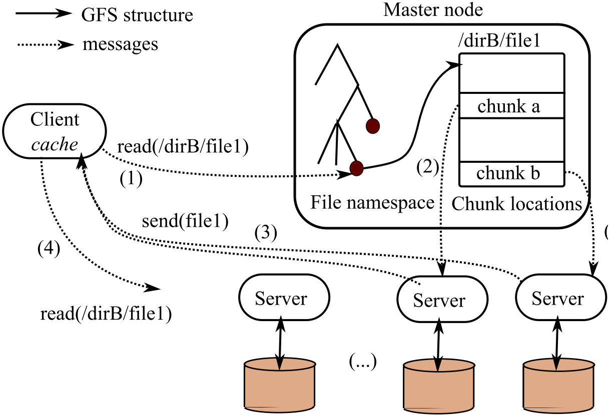
Fact: standard NFS (left part) does not meet scalability requirements (what if `file1` gets really big?).



Right part: GFS/HDFS storage, based on (i) a virtual file namespace, and (ii) partitioning of files in “chunks”.

Architecture

A Master node performs administrative tasks, while servers store "chunks" and send them to Client nodes.



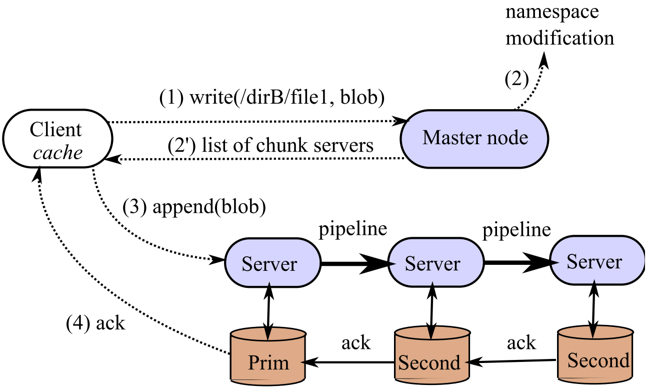
The Client maintains a cache with chunks locations, and directly communicates with servers.

Technical details

- The architecture works best for very large files (e.g., several Gigabytes), divided in large (64-128 MBs) chunks. $\Rightarrow$ this limits the metadata information served by the Master.
- Each server implements recovery and replication techniques (default: 3 replicas).
- (Availability) The Master sends heartbeat messages to servers, and initiates a replacement when a failure occurs.
- (Scalability) The Master is a potential single point of failure; its protection relies on distributed recovery techniques for all changes that affect the file namespace.

Workflow of a *write()* operation (simplified)

The following figure shows a non-concurrent *append()* operation.

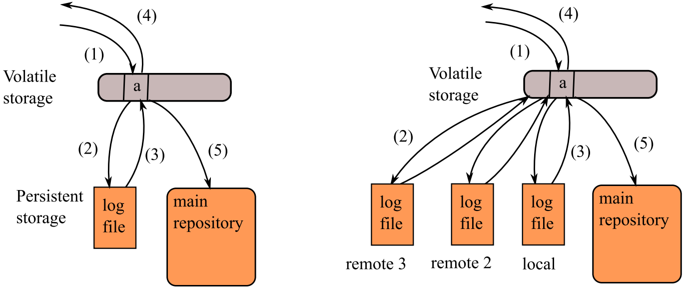


Write (append) in GFS (simplified to non-concurrent operations)

In case of concurrent appends to a chunk, the primary replica assigns serial numbers to the mutation, and coordinates the secondary replicas.

Namespace updates: distributed recovery protocol

Extension of standard techniques for recovery (left: centralized; right: distributed).



If a node fails, the replicated log file can be used to recover the last transactions on one of its mirrors.

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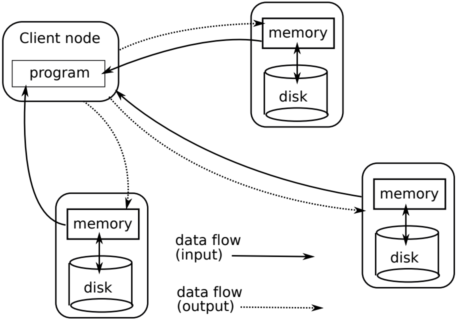
Data analysis at very large scale

- Very large data collections (dozen of TBs to EB) stored on distributed filesystems:
    - Crawl data
    - Query logs
    - Search engine indexes
    - Sensor data
- Need efficient ways for analyzing, reformatting, processing them
- In particular, we want:
    - Parallelization of computation (benefiting of the processing power of all nodes in a cluster)
    - Resilience to failure

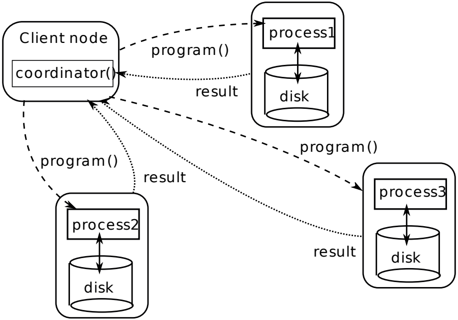
Centralized computing with distributed data storage

Run the program at client node, get data from the distributed system.



Downsides: important data flows, no use of the cluster computing resources.

Pushing the program near the data



- MapReduce: A programming model (inspired by standard functional programming operators) to facilitate the development and execution of distributed tasks.
- Published by Google Labs in 2004 at OSDI [DG04]. Widely used since then, open-source implementation in Hadoop.

MapReduce in Brief

- The programmer defines the program logic as two functions:
  - **Map** transforms the input into key-value pairs to process
  - **Reduce** aggregates the list of values for each key
- The MapReduce environment takes in charge distribution aspects
- A complex program can be decomposed as a succession of Map and Reduce tasks
- Higher-level languages (Pig, Cascading, Hive, etc.) help with writing distributed applications

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Three operations on key-value pairs

1. User-defined: $map : (K, V) \to \text{list}(K', V')$

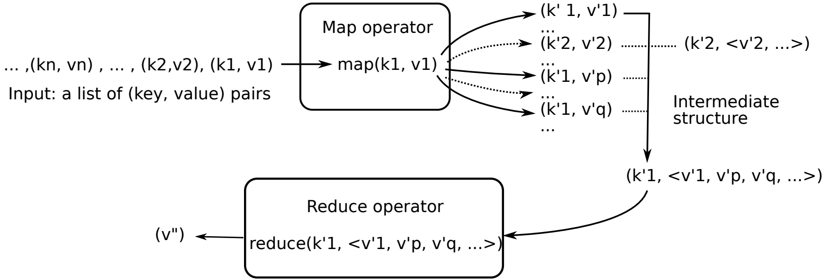
```
function map(uri, document)
  foreach distinct term in document
    output (term, count(term, document))
```

2. Fixed behavior: $shuffle : \text{list}(K', V') \to \text{list}(K', \text{list}(V'))$ regroups all intermediate pairs on the key
3. User-defined: $reduce : (K', \text{list}(V')) \to \text{list}(K'', V'')$

```
function reduce(term, counts)
  output (term, sum(counts))
```

Job workflow in MapReduce

Important: each pair, at each phase, is processed independently from the other pairs.



Network and distribution are transparently managed by the MapReduce environment.

Example: term count in MapReduce (input)

URL	Document
u_1	the jaguar is a new world mammal of the felidae family.
u_2	for jaguar, atari was keen to use a 68k family device.
u_3	mac os x jaguar is available at a price of us $199 for apple's new "family pack".
u_4	one such ruling family to incorporate the jaguar into their name is jaguar paw.
u_5	it is a big cat.

Example: term count in MapReduce

term	count
jaguar	1
mammal	1
family	1
jaguar	1
available	1
jaguar	1
family	1
family	1
jaguar	2
...	

map output
shuffle input

Example: term count in MapReduce

term	count
jaguar	1
mammal	1
family	1
jaguar	1
available	1
jaguar	1
family	1
family	1
jaguar	2
...	

map output
shuffle input

term	count
jaguar	1,1,1,2
mammal	1
family	1,1,1
available	1
...	

shuffle output
reduce input

Example: term count in MapReduce

term	count
jaguar	1
mammal	1
family	1
jaguar	1
available	1
jaguar	1
family	1
family	1
jaguar	2
...	

map output
shuffle input

term	count
jaguar	1,1,1,2
mammal	1
family	1,1,1
available	1
...	

shuffle output
reduce input

term	count
jaguar	5
mammal	1
family	3
available	1
...	

final output

Example: simplification of the *map*

```
function map(uri, document)
  foreach distinct term in document
    output (term, count(term, document))
```

can actually be further simplified:

```
function map(uri, document)
  foreach term in document
    output (term, 1)
```

since all counts are aggregated.

Might be less efficient though (we may need a combiner, see further)

A MapReduce cluster

Nodes inside a MapReduce cluster are decomposed as follows:

- A jobtracker acts as a master node; MapReduce jobs are submitted to it
- Several tasktrackers run the computation itself, i.e., *map* and *reduce* tasks
- A given tasktracker may run several tasks in parallel
- Tasktrackers usually also act as data nodes of a distributed filesystem (e.g., GFS, HDFS)

+ a client node where the application is launched.

Processing a MapReduce job

A MapReduce job takes care of the distribution, synchronization and failure handling. Specifically:

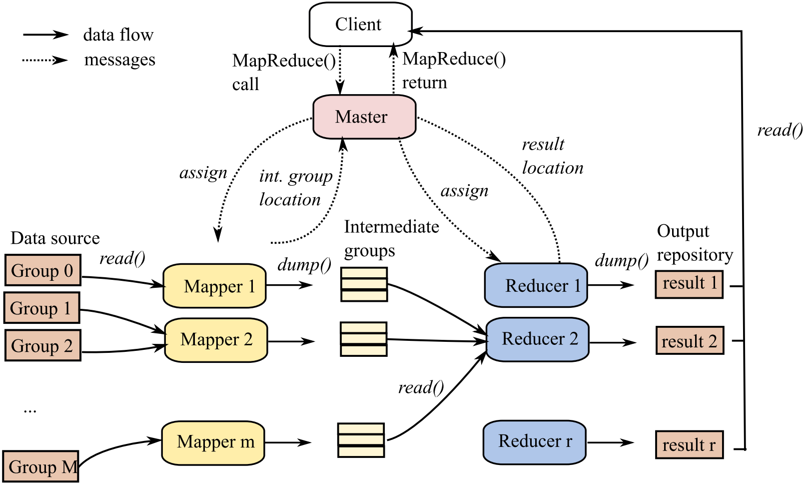
- the input is split into M groups; each group is assigned to a mapper (assignment is based on the data locality principle)
- each mapper processes a group and stores the intermediate pairs locally
- grouped instances are assigned to reducers thanks to a hash function
- (*shuffle*) intermediate pairs are sorted on their key by the reducer
- one obtains grouped instances, submitted to the *reduce* function

Remark: the data locality does no longer hold for the *reduce* phase, since it reads from the mappers.

Assignment to reducer and mappers

- Each mapper task processes a fixed amount of data (split), usually set to the distributed filesystem block size (e.g., 64 MB)
- The number of mapper nodes is function of the number of mapper tasks and the number of available nodes in the cluster: each mapper nodes can process (in parallel and sequentially) several mapper tasks
- Assignment to mapper tries optimizing data locality: the mapper node in charge of a split is, if possible, one that stores a replica of this split (or if not possible, a node of the same rack)
- The number of reducer tasks is set by the user
- Assignment to reducers is done through a hashing of the key, usually uniformly at random; no data locality possible

Distributed execution of a MapReduce job.



Processing the term count example

Let the input consists of documents, say, one billion 100-terms documents of approximately 1 KB each.

Assume the split operation distributes these documents in groups of 64 MB: each group consists of 64,000 documents. Therefore $M = \lceil 1\,000\,000\,000/64\,000 \rceil \approx 16\,000$ groups.

If there are 1 000 mapper nodes, each node processes on average 16 splits.

If there are 1 000 reducers, each reducer r_i processes all key-value pairs for terms t such that $hash(t) = i$ $(1 \leqslant i \leqslant 1\,000)$

Processing the term count example (2)

Assume that $hash(\text{'call'}) = hash(\text{'mine'}) = hash(\text{'blog'}) = i = 100$. We focus on three Mappers m_p, m_q and m_r:

1. $G_i^p = (<\ldots, (\text{'mine'}, 1), \ldots, (\text{'call'},1), \ldots, (\text{'mine'},1), \ldots, (\text{'blog'}, 1) \ldots >$
2. $G_i^q = (< \ldots, (\text{'call'},1), \ldots, (\text{'blog'},1), \ldots >$
3. $G_i^r = (<\ldots, (\text{'blog'}, 1), \ldots, (\text{'mine'},1), \ldots, (\text{'blog'},1), \ldots >$

r_i reads G_i^p, G_i^p and G_i^p from the three Mappers, sorts their unioned content, and groups the pairs with a common key:

$$\ldots, (\text{'blog'}, <1, 1, 1, 1>), \ldots, (\text{'call'}, <1, 1>), \ldots, (\text{'mine'}, <1, 1, 1>)$$

Our *reduce* function is then applied by r_i to each element of this list. The output is *('blog', 4), ('call', 2) and ('mine', 3)*

Failure management

In case of failure, because the tasks are distributed over hundreds or thousands of machines, the chances that a problems occurs somewhere are much larger; starting the job from the beginning is not a valid option.

The Master periodically checks the availability and reachability of the tasktrackers (heartbeats) and whether *map* or *reduce* jobs make any progress

1. if a reducer fails, its task is reassigned to another tasktracker, intermediate groups are sent over from mappers
2. if a mapper fails, its task is reassigned to another tasktracker
3. if the jobtracker fails, the whole job should be re-initiated

Joins in MapReduce

Two datasets, A and B that we need to join for a MapReduce task

- If one of the dataset is small, it can be sent over fully to each tasktracker and exploited inside the *map* (and possibly *reduce*) functions
- Otherwise, each dataset should be grouped according to the join key, and the result of the join can be computing in the *reduce* function

Not very convenient to express in MapReduce. Much easier in higher-level languages.

Using MapReduce for solving a problem

- Prefer:
  - Simple *map* and *reduce* functions
  - Mapper tasks processing large data chunks (at least the size of distributed filesystem blocks)
- A given application may have:
  - A chain of *map* functions (input processing, filtering, extraction...)
  - A sequence of several *map-reduce* jobs
  - No *reduce* task when everything can be expressed in the *map* (zero reducers, or the identity reducer function)
- Not the right tool for everything (see further)

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Alternative Distributed Computation Models

Combiners

- A mapper task can produce a large number of pairs with the same key
- They need to be sent over the network to the reducer: costly
- It is often possible to combine these pairs into a single key-value pair
  (jaguar,1), (jaguar, 1), (jaguar, 1), (jaguar, 2)→(jaguar, 5)
- *combiner* : $\text{list}(V') \rightarrow V'$ function executed (possibly several times) to combine the values for a given key, on a mapper node
- No guarantee that the *combiner* is called
- Easy case: the combiner is the same as the *reduce* function. Possible when the aggregate function α computed by *reduce* is distributive: $\alpha(k_1, \alpha(k_2, k_3)) = \alpha(k_1, k_2, k_3)$

Compression

- Data transfers over the network:
    - From datanodes to mapper nodes (usually reduced using data locality)
    - From mappers to reducers
    - From reducers to datanodes to store the final output
- Each of these can benefit from data compression
- Trade-off between volume of data transfer and (de)compression time
- Usually, compressing *map* outputs using a fast compressor increases efficiency

Optimizing the *shuffle* operation

- Sorting of pairs on each reducer, to compute the groups: costly operation
- Sorting much more efficient in memory than on disk
- Increasing the amount of memory available for *shuffle* operations can greatly increase the performance
- ... at the downside of less memory available for *map* and *reduce* tasks (but usually not much needed)

Speculative execution

- The MapReduce jobtracker tries detecting tasks that take longer than usual (e.g., because of hardware problems)
- When detected, such a task is speculatively executed on another tasktracker, without killing the existing task
- Eventually, when one of the attempts succeeds, the other one is killed

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Hadoop

- Open-source software, Java-based, managed by the Apache foundation, for large-scale distributed storage and computing
- Originally developed for Apache Nutch (open-source Web search engine), a part of Apache Lucene (text indexing platform)
- Open-source implementation of GFS and Google's MapReduce
- Yahoo!: a main contributor of the development of Hadoop

Hadoop components

- Hadoop filesystem (HDFS)
- MapReduce
- Pig (data exploration), Hive (data warehousing): higher-level languages for describing MapReduce applications
- HBase: column-oriented distributed DBMS
- ZooKeeper: coordination service for distributed applications

Hadoop programming interfaces

- Different APIs to write Hadoop programs:
  - A rich Java API (main way to write Hadoop programs)
  - A Streaming API that can be used to write *map* and *reduce* functions in any programming language (using standard inputs and outputs)
  - A C++ API (Hadoop Pipes)
  - With a higher-language level (e.g., Pig, Hive, Cascading)
- Advanced features only available in the Java API, but the streaming API is good enough for most uses

Python *map* for the term count example

```
import sys

for line in sys.stdin:
    line = line.strip()
    words = line.split()
    for word in words:
        print('%s\t%s' % (word, 1))
```

Python *reduce* for the term count example

```
import sys

c = dict()

for line in sys.stdin:
    line = line.strip()
    word, count = line.split('\t', 1)
    count = int(count)
    if word in c:
        c[word] += count
    else:
        c[word] = count

for w in c:
    print('%s\t%s' % (w, c[w]))
```

Command line to run the streaming API

```
hadoop jar hadoop-streaming-*.jar \
  -files mapper.py,reducer.py \
  -mapper mapper.py \
  -reducer reducer.py \
  -input 'input_directory/*' \
  -output output_directory
```

Testing and executing a Hadoop job

- Required environment:
  - JDK on client
  - JRE on all Hadoop nodes
  - Hadoop distribution (HDFS + MapReduce) on client and all Hadoop nodes
  - SSH servers on each tasktracker, SSH client on jobtracker (used to control the execution of tasktrackers)
  - An IDE (e.g., Eclipse + plugin) on client
- Three different execution modes:

  local One mapper, one reducer, run locally from the same JVM as the client

  pseudo-distributed mappers and reducers are launched on a single machine, but communicate over the local network

  distributed over a cluster for real runs

Debugging MapReduce

- Easiest: debugging in local mode
- Web interface with status information about the job
- Standard output and error channels saved on each node, accessible through the Web interface
- Counters can be used to track side information across a MapReduce job (e.g., number of invalid input records)
- Remote debugging possible but complicated to set up (impossible to know in advance where a *map* or *reduce* task will be executed)

Hadoop in the cloud

- Possibly to set up one's own Hadoop cluster
- But often easier to use clusters in the cloud that support MapReduce:
  - Amazon EMR
  - Google Cloud Dataproc
  - Cloudera CDH
  - etc.
- Not always easy to know the cluster's configuration (in terms of racks, etc.) when on the cloud, which hurts data locality in MapReduce

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MapReduce limitations (1/2)

- High latency. Launching a MapReduce job has a high overhead, and *reduce* functions are only called after all *map* functions succeed, not suitable for applications needing a quick result.
- Batch processing only. MapReduce excels at processing a large collection, not at retrieving individual items from a collection.
- Write-once, read-many mode. No real possibility of updating a dataset using MapReduce, it should be regenerated from scratch
- No transactions. No concurrency control at all, completely unsuitable for transactional applications [PPR+09].

MapReduce limitations (2/2)

- Relatively low-level. Some efforts for more high-level languages: Scope [CJL+08], Pig [ORS+08, GNC+09], Hive [TSJ+09], Cascading `http://www.cascading.org/`
- No structure. Implies lack of indexing, difficult to optimize, etc. [DS87]
- Hard to tune. Number of reducers? Compression? Memory available at each node? etc.

Job Scheduling

- Multiple jobs concurrently submitted to the MapReduce jobtracker
- Fair scheduling required:
  - each submitted job should have some share of the cluster
  - prioritization of jobs
  - long-standing jobs should not block quick jobs
  - fairness with respect to users
- Standard Hadoop scheduler: priority queue
- Hadoop Fair Scheduler: ensures cluster resources are shared among users. Preemption (= killing running tasks) possible in case the sharing becomes unbalnaced.

What you should remember on distributed computing

MapReduce is a simple model for batch processing of very large collections.
⇒ good for data analytics; not good for point queries (high latency).

The systems brings robustness against failure of a component and transparent distribution and scalability.
⇒ more expressive languages required (Pig)

Resources

- Original description of the MapReduce framework [DG04]
- Hadoop distribution and documentation available at `http://hadoop.apache.org/`
- Excellent textbook on Hadoop [Whi09]

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Alternative Distributed Computation Models

- Apache Hive: SQL Analytics on MapReduce
- Apache Storm: Real-Time Computation
- Apache Spark: More Complex Workflows
- Pregel, Apache Giraph, GraphLab: Think as a Vertex

Apache Hive

- Data warehousing on top of Hadoop
- SQL-like language to express high-level queries, esp., aggregate and analytics
- Queries translated into Map–Reduce jobs (or Spark jobs, see further)
- Similar to Pig (which is now a bit obsolete), but declarative vs imperative, and geared towards analytics vs transformation of datasets; dataflow more obvious in Pig programs

Term count in Hive

```
CREATE TABLE doc(text STRING)
ROW FORMAT DELIMITED FIELDS TERMINATED BY '\n'
STORED AS TEXTFILE;

LOAD DATA INPATH 'hdfs://input.txt'
  INTO TABLE doc;

SELECT word, COUNT(*)
FROM doc
  LATERAL VIEW EXPLODE(SPLIT(text, '␣')) temp
  AS word
GROUP BY word;
```

Term count in Pig

```
a = load 'hdfs://input.txt' as (line: chararray);
b = foreach a generate flatten(TOKENIZE(line))
  as word;
c = group b by word;
d = foreach c generate COUNT(b), group;
dump d;
```

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Apache Storm

- Real-time analytics, in opposition to the batch model of MapReduce
- Achieves very reasonable latency
- Process data in a streaming fashion
- Based on the notion of event producer (spout) and manipulation (bolt)
- Written in Clojure (Lisp) + Java, jobs usually written in Java

Term count in Storm

```
Config config = new Config();
config.put("inputFile", args[0]);
TopologyBuilder builder = new TopologyBuilder();
builder.setSpout("line-reader-spout",
                 new LineReaderSpout());
builder.setBolt("word-spitter", new WordSplitterBolt()).
  shuffleGrouping("line-reader-spout");
builder.setBolt("word-counter", new WordCounterBolt()).
  shuffleGrouping("word-spitter");
LocalCluster cluster = new LocalCluster();
cluster.submitTopology("HelloStorm", config,
                       builder.createTopology());
```

Only the driver, the spouts and the bolts also need to be defined!

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Apache Spark

- Similar positioning as Pig: high-level language with a dataflow of operators
- Many more operators than Pig
- Complex programs can be written in Scala, Java, or Python
- Contrarily to Pig, jobs are not translated to MapReduce, but executed directly in a distributed fashion
- Based on RDDs (Resilient Distributed Dataset) that can be HDFS files, HBase tables, or the result of applying a succession of operators on these
- Contrarily to MapReduce, local workers have the ability to keep data in memory in a succession of tasks
- Extensions allowing to perform streaming data processing, to process Hive SQL queries
- MLLib: machine learning library on top of Spark

Term count in Spark (Python)

```
file = spark.textFile("hdfs://input.txt")
counts = file \
  .flatMap(lambda line: line.split("␣")) \
  .map(lambda word: (word, 1)) \
  .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://output.txt")
```

Outline

Distributed Data Systems

MapReduce

Limitations of MapReduce

Alternative Distributed Computation Models

- Apache Hive: SQL Analytics on MapReduce
- Apache Storm: Real-Time Computation
- Apache Spark: More Complex Workflows
- Pregel, Apache Giraph, GraphLab: Think as a Vertex

Graph Computation Frameworks

- Parallel computation on graph-like data (Web graph, social networks, transportation networks, etc.)
- Pregel: original system by Google
- Apache Giraph: open-source clone of Pregel
- GraphLab: similar goals, different architecture
- One writes vertex programs: each vertex receives messages and sends messages to its neighbours
- Pregel and Giraph are based on the bulk synchronous parallel paradigm: synchronization barrier once vertex programs are executed on every vertex
- GraphLab uses an asynchronous model

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