MapReduce: Apache Hadoop

Big Data Management

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October 8, 2019

Borrowed from http://www.ksi.mff.cuni.cz/~svoboda/courses/171-NDBI040/

Lecture Outline

NoSQL and RBDMS

MapReduce

- Programming model and implementation
- Motivation, principles, details, ...

Apache Hadoop

- HDFS – Hadoop Distributed File System
- MapReduce

NoSQL and RBDMS

Drawbacks of RDBMS

- Database system are **difficult** to **scale**
- Database systems are **difficult** to **configure** and **maintain**
- **Diversification** in available systems **complicates** its selection
- **Peak provisioning** leads to **unnecessary costs**

Advantages of NoSQL systems

- Elastic **scaling**
- Less **administration**
- Better **economics**
- **Flexible** data models

NoSQL and Batch Systems

NoSQL drops a lot of functionality of RDBMS

- no real **data dictionaries**, but semi-structured models for providing **meta-data**
- **hard** to access without **explicit knowledge** of the data model
- Transaction processing cmp. CAP-theorem
- often **limited** access control (no user groups, roles)
- **limited** indexing/efficiency is most **replaced** with scalability

So what's left:

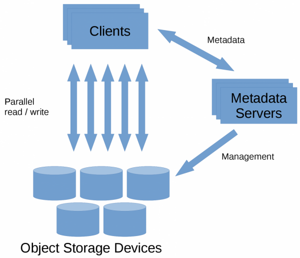
- **storing** massive amount of data in **cluster** environments (sharding and replication)
- **eventual** consistency (at some point after the change every instance of the data is replication consistent
- some database like APIs (e.g., CQL)

But then: What's makes the DBMS so much different from a File-System?

Distributed File Systems

Distributed File Systems

- majority of **analysis** is still run on **files**
- machine learning, statistics and data mining methods usually **access** all available data
- require a **well-defined input** and **not semi-structured** objects (data cleaning, transformation...)
  1. **Scalable** data analytics often suffices with a distributed file system
  2. **Parallelized** on top of the distributed file systems



Distributed File Systems

Past

- most computing is done on a **single processor**
  - one main memory, one cache, one local disk, ...

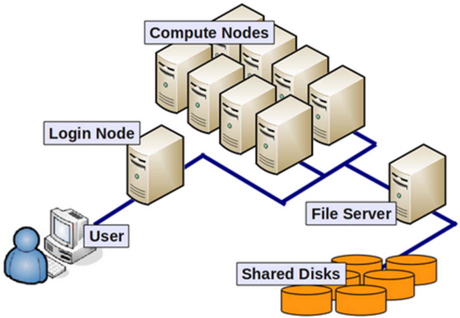
New Challenges

1. Files must be **stored** **redundantly**
   - If one node fails, all of its files would be **unavailable** until the node is **replaced**
2. **Computations** must be **divided** into **tasks**
   - a task can be **restarted** **without affecting** other tasks
3. use of **commodity** hardware

Distributed File Systems

Parallel computing architecture

- Referred to as cluster computing
- Physical Organization
  - **compute nodes** are stored on **racks** (8-64)
  - nodes on a single rack **connected** by a network



Distributed File Systems

Large-Scale File-System Organization

- **Characteristics**
  1. files are **several terabytes** in size (Facebook's daily logs: 60TB; 1000 genomes project: 200TB; Google Web Index; 10+ PB)
  2. files are **rarely updated**
  3. reads and **appends** are **common**
- Exemplary distributed file systems
  - Google File System (GFS)
  - Hadoop Distributed File System (HDFS, by Apache)
  - CloudStore
  - HDF5
  - S3 (Amazon EC2)
  - ...

Distributed File Systems

Large-Scale File-System Organisation

1. files are **divided** into **chunks** (typically 16-64MB in size)
2. chunks are **replicated** n times
    - i.e **default** in HDFS: n=3, at n different nodes
    - optimally: replicas are located on different racks optimising **fault tolerance**

How to find files?

- existence of a **master node**
- holds a **meta-file** (directory) about **location** of **all copies** of a file
    - all participants using the DFS know where copies are located

Programming Models

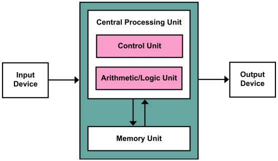
What is a programming model?

- **Abstraction** of an underlying computer system
  - Describes a **logical view** of the provided **functionality**
  - Offers a **public** **interface**, **resources** or **other constructs**
  - Allows for the **expression** of **algorithms** and **data structures**
  - Conceals physical reality of the **internal** implementation
  - Allows working at a (much) **higher** **level of abstraction**
- The point is
  - how the intended user thinks in order **to solve** their tasks
  - and **not** necessarily how the system **actually works**

Programming Models

Examples

- Traditional von Neumann model
  - **Architecture** of a physical computer with several components such as a central processing unit (CPU), arithmetic-logic unit (ALU), processor registers, program counter, memory unit, etc.
  - **Execution** of a stream of instructions



- Java Virtual Machine (JVM)
- ...

Do not confuse programming models with

- Programming paradigms (procedural, functional, logic, modular, object-oriented, recursive, generic, data-driven, parallel, ...)
- Programming languages (Java, C++, ...)

Parallel Programming Models

Process interaction. Mechanisms of mutual communication of parallel processes

- **Shared memory** – shared global address space, asynchronous read and write access, synchronization primitives
- **Message passing**
- **Implicit interaction**

Problem decomposition. Ways of problem decomposition into tasks executed in parallel

- **Task parallelism**
- **Data parallelism** – independent tasks on disjoint partitions of data
- **Implicit parallelism**

MapReduce

What is MapReduce?

- **Programming model + implementation**
- Developed by Google in 2008
- A **simple** and **powerful** **interface** that enables **automatic parallelization** and **distribution** of large-scale computations,
- combined with an **implementation** of this interface that achieves **high performance** on **large clusters** of commodity PCs

MapReduce Framework

A bit of history and motivation **Google PageRank problem (2003)**

- How to rank tens of billions of web pages by their importance?
  - **efficiently** in a reasonable amount of time
  - when data is **scattered** across thousands of computers
  - data files can be **enormous** (terabytes or more)
  - data files are **updated** only **occasionally** (just appended)
  - **sending** the data between compute nodes is **expensive**
  - **hardware failures** are rule rather than exception
- **Centralized index** structure was no longer sufficient
- Solution
  - **Google File System** – a distributed file system
  - **MapReduce** – a programming model

MapReduce Framework

MapReduce programming model

- **Cluster** of commodity personal computers (nodes)
  - Each running a **host** operating system,
  - **mutually interconnected** within a network,
  - **communication** based on IP addresses, ...
- **Data** is **distributed** among the nodes
- **Tasks** executed in **parallel** across the nodes

Classification

- **Process interaction:** message passing
- **Problem decomposition:** data parallelism

MapReduce Model: Basic Idea

Divide-and-conquer paradigm

- **Map function**
  - Breaks down a **problem** into **sub-problems**
  - Processes input data **in order** to generate a set of **intermediate** key-value pairs
- **Reduce function**
  - Receives and combines **sub-solutions** to solve the problem
  - Processes and possibly reduces intermediate values associated with the same intermediate key And that's all!

MapReduce Model: Basic Idea

It means...

- We **only** need to **implement** Map and Reduce functions
- Everything else such as
  - input data **distribution**,
  - **scheduling** of execution tasks,
  - **monitoring** of computation progress,
  - inter-machine **communication**,
  - handling of machine **failures**,
  - ...
- is **managed automatically** by the framework!

MapReduce Model: A bit more formally

Map function

- **Input:** an input **key-value pair** (input record)
- **Output:** a set of **intermediate key-value pairs**
  - Usually from a **different domain**
  - Keys do not have to be unique
- (key, value) $\rightarrow$ list of (key, value)

Reduce function

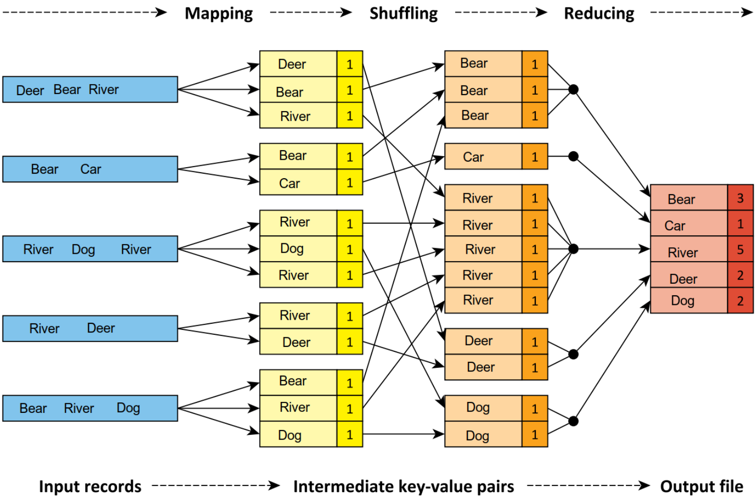
- **Input:** an intermediate key + a set of (all) values for this key
- **Output:** a possibly **smaller set of values** for this key
  - From the **same domain**
- (key, list of values) $\rightarrow$ (key, list of values)

Example: Word Frequency

Implementation

```
/**
* Map function
* @param key Document identifier
* @param value Document contents
*/
map(String key, String value) {
  foreach word w in value: emit(w, 1);
}
/**
* Reduce function
* @param key Particular word
* @param values List of count values generated for this word
*/
reduce(String key, Iterator values) {
  int result = 0;
  foreach v in values: result += v;
  emit(key, result);
}
```

Logical Phases



Logical Phases

Mapping phase

- Map function is **executed** for **each input** record
- **Intermediate** key-value pairs are **emitted**

Shuffling phase

- Intermediate key-value pairs are **grouped** and **sorted** according to the keys

Reducing phase

- Reduce function is **executed** for **each intermediate** key
- **Final output** is **generated**

Framework Architecture

Master-slave architecture

- **Master**
  - **Manages** the entire execution of MapReduce jobs
  - **Schedules** individual Map/Reduce tasks to idle workers
- **Slave (worker)**
  - **Accepts** Map/Reduce tasks from the master

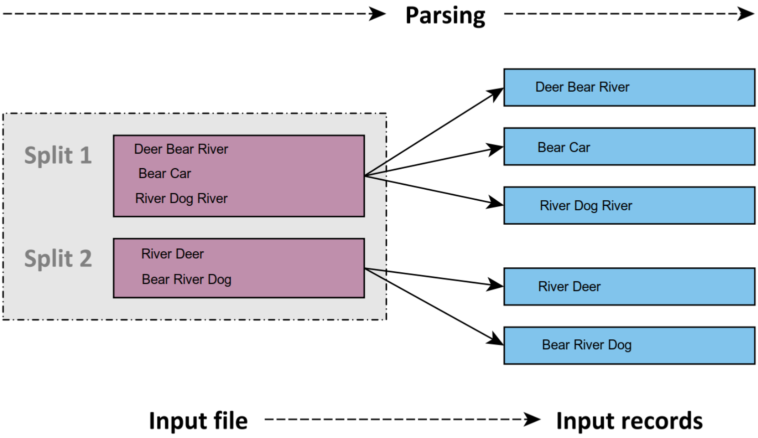
Input/output files

- **Stored** in the underlying distributed file system
- **Actual contents** of these files...
  - **Divided** into smaller **splits**
  - Physically **stored** by individual slaves

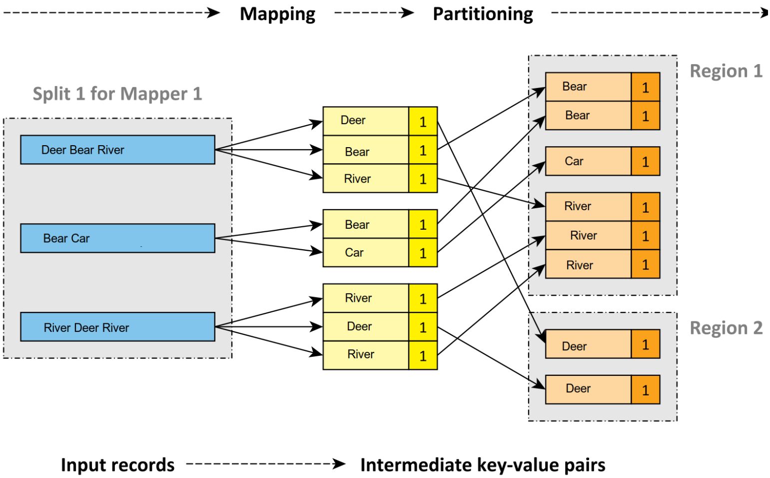
Input Parsing

Parsing phase

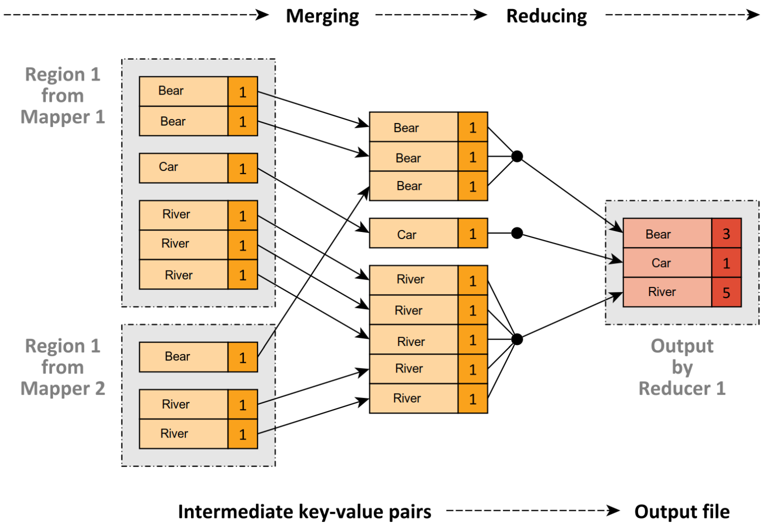
- Each split is **parsed** so that input records are **retrieved**
- i.e. input key-value pairs are obtained



Mapping Phase



Reducing Phase



Execution Functions

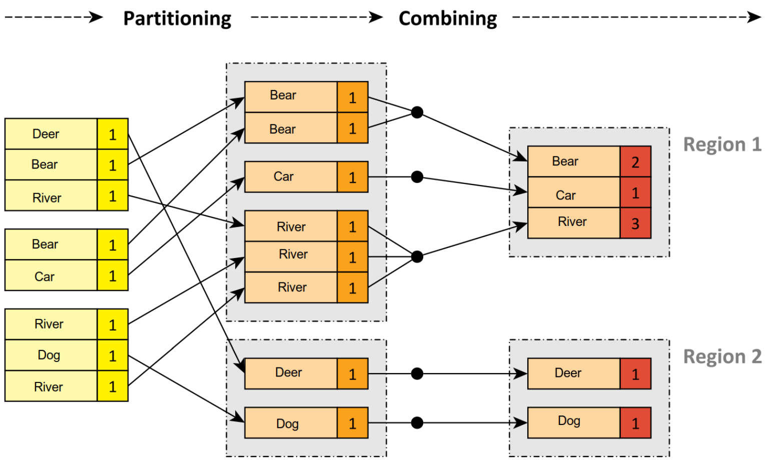
1. **Input reader**
   - Parses a given input split and prepares input records
2. **Map function**
3. **Partition function**
   - Determines a particular Reducer for a given intermediate key
4. **Compare function**
   - Mutually compares two intermediate keys
5. **Combine function**
6. **Reduce function**
7. **Output writer**
   - Writes the output of a given Reducer

Combine Function

Optional Combine function

- Analogous purpose and implementation to the Reduce function
- **Objective.** Decrease the amount of **intermediate** data
  - i.e. decrease the amount of data transferred to Reducers
- **Executed** locally by Mapper before the shuffling phase
- Only works for **commutative** and **associative** functions!

Combine Function



Intermediate key-value pairs

Advanced Aspects

Counters

- Allow to **track** the progress of a MapReduce job in real time
- **Predefined counters**
  - e.g. numbers of launched/finished Map/Reduce tasks, parsed input key-value pairs, ...
- **Custom counters** (user-defined)
  - Can be associated with any action that a Map or Reduce function does

Advanced Aspects

Fault tolerance

- When a large number of nodes process a large number of data *Rightarrow* fault tolerance is necessary

Worker failure

- Master **periodically pings** every worker; if no response is received in a certain amount of time, master marks the worker as **failed**
- All its tasks are **reset** back to their **initial idle state** and become **eligible** for **rescheduling** on other workers

Master failure

- **Strategy A** – **periodic checkpoints** are created; if master fails, a new copy can then be started
- **Strategy B** – master failure is considered to be highly **unlikely**; users simply **resubmit unsuccessful jobs**

Advanced Aspects

Stragglers

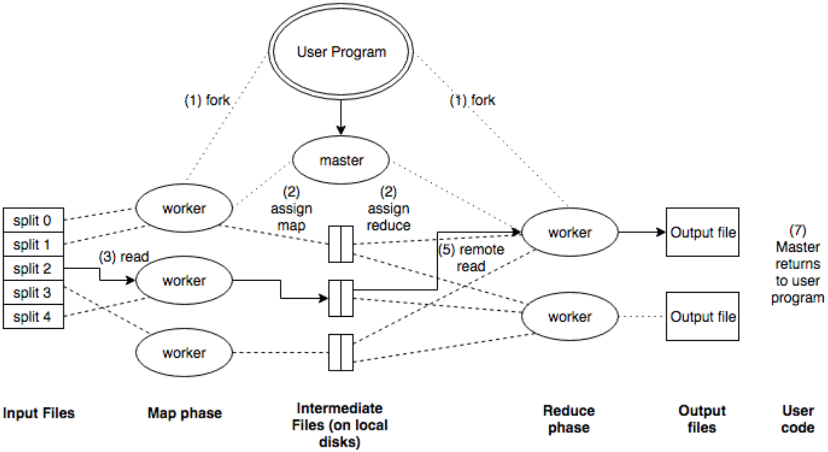
- **Straggler** = node that **takes unusually long time** to complete a task it was assigned
- Solution
  1. When a MapReduce job is close to completion, the master schedules backup executions of the remaining in-progress tasks
  2. A given task is considered to be completed whenever either the **primary** or the **backup** execution **completes**

Advanced Aspects

Task granularity

- Intended **numbers of** Map and Reduce tasks
- Practical recommendation (by Google)
  1. Map tasks
     - Choose the number so that each individual Map task has roughly **16–64 MB** of input data
  2. Reduce tasks
     - Use a **small multiple** of the number of worker nodes
     - Output of each Reduce task ends up in a **separate output file**

Combine Function



Additional Examples

URL access frequency

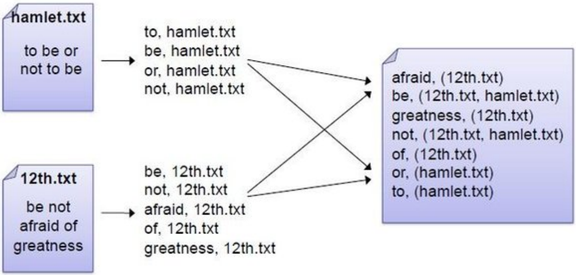
- **Input:** HTTP server access logs
- **Map:** parses a log, emits (accessed URL, 1) pairs
- **Reduce:** computes and emits the sum of the associated values
- **Output:** overall number of accesses to a given URL

```
/**
* Map function
* @param key log name
* @param value log contents
*/
map(String key, String value) {
  foreach line l in value: emit(URL(l), 1);
}
/**
* Reduce function
* @param key URL
* @param values List of count values generated for this URL
*/
reduce(String key, Iterator values) {
  int result = 0;
  foreach v in values: result += v;
  emit(key, result);
}
```

Additional Examples

Inverted index

- **Input:** text documents containing words
- **Map:** parses a document, emits (word, document ID) pairs
- **Reduce:** emits all the associated document IDs sorted
- **Output:** list of documents containing a given word



Additional Examples

Distributed sort

- **Input:** records to be sorted according to a specific criterion
- **Map:** extracts the sorting key, emits (key, record) pairs
- **Reduce:** emits the associated records unchanged

Reverse web-link graph

- **Input:** web pages with ... tags
- **Map:** emits (target URL, current document URL) pairs
- **Reduce:** emits the associated source URLs unchanged
- **Output:** list of URLs of web pages targeting a given one

Additional Examples

Sources of links between web pages

```
/**
* Map function
* @param key Source web page URL
* @param value HTML contents of this web page
*/
map(String key, String value) {
  foreach <a> tag t in value: emit(t.href, key);
}
```

```
/**
* Reduce function
* @param key URL of a particular web page
* @param values List of URLs of web pages targeting this one
*/
reduce(String key, Iterator values) {
  emit(key, values);
}
```

Use Cases: General Patterns

Counting, summing, aggregation

- When the overall **number of occurrences** of certain items or a different aggregate function should be calculated

Collating, grouping

- When all items **belonging to** a certain group should be **found**, collected together or processed in another way

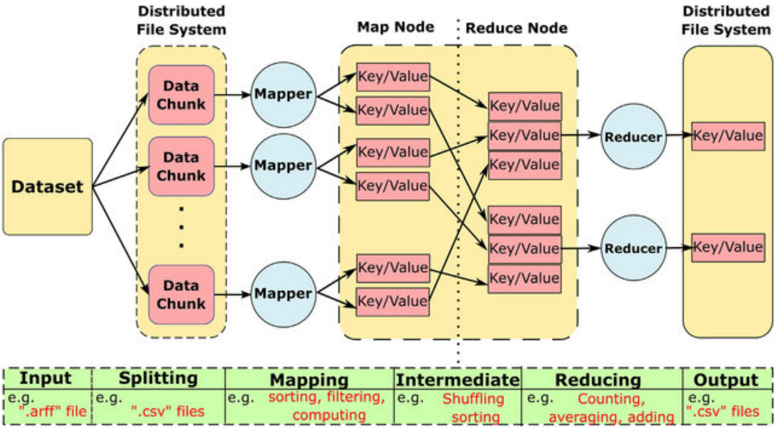
Filtering, querying, parsing, validation

- When all items **satisfying** a certain condition should be found, transformed or processed in another way

Sorting

- When items should be processed in a **particular order** with respect to a certain ordering criterion

Use Cases: General Patterns



Use Cases: Real-World Problems

Just a few real-world examples ...

- Risk modeling, customer churn
- Recommendation engine, customer preferences
- Advertisement targeting, trade surveillance
- Fraudulent activity threats, security breaches detection
- Hardware or sensor network failure prediction
- Search quality analysis
- ...

Source: http://www.cloudera.com/

Apache Hadoop

Open-source software framework

- http://hadoop.apache.org/
- Distributed **storage** and **processing** of very **large data sets** on **clusters** built from commodity hardware
  - Implements a **distributed file system**
  - Implements a **MapReduce programming model**
- Derived from the original Google MapReduce and GFS
- Developed by Apache Software Foundation
- Implemented in Java
- Operating system: cross-platform
- Initial release in 2011

Apache Hadoop

Modules

1. **Hadoop Common**
   - Common utilities and support for other modules
2. **Hadoop Distributed File System (HDFS)**
   - High-throughput distributed file system
3. **Hadoop Yet Another Resource Negotiator (YARN)**
   - Cluster resource management
   - Job scheduling framework
4. **Hadoop MapReduce**
   - YARN-based implementation of the MapReduce model

Apache Hadoop

Hadoop-related projects

- Apache Cassandra – wide column store
- Apache HBase – wide column store
- Apache Hive – data warehouse infrastructure
- Apache Avro – data serialization system
- Apache Chukwa – data collection system
- Apache Mahout – machine learning and data mining library
- Apache Pig – framework for parallel computation and analysis
- Apache ZooKeeper – coordination of distributed applications
- ...

Apache Hadoop

Real-world Hadoop users

1. Facebook – internal logs, analytics, machine learning, 2 clusters
   - 1100 nodes (8 cores, 12 TB storage), 12 PB
   - 300 nodes (8 cores, 12 TB storage), 3 PB
2. LinkedIn – 3 clusters
   - 800 nodes (2×4 cores, 24 GB RAM, 6×2 TB SATA), 9 PB
   - 1900 nodes (2×6 cores, 24 GB RAM, 6×2 TB SATA), 22 PB
   - 1400 nodes (2×6 cores, 32 GB RAM, 6×2 TB SATA), 16 PB
3. Spotify – content generation, data aggregation, reporting, analysis
   - 1650 nodes, 43000 cores, 70 TB RAM, 65 PB, 20000 daily jobs
4. Yahoo! – 40000 nodes with Hadoop, biggest cluster
   - 4500 nodes (2×4 cores, 16 GB RAM, 4×1 TB storage), 17 PB

Source: `http://wiki.apache.org/hadoop/PoweredBy`

HDFS

Hadoop Distributed File System

- Open-source, high quality, cross-platform, pure Java
- Highly scalable, high-throughput, fault-tolerant
- Master-slave architecture
- **Optimal applications**
  - MapReduce, web crawlers, data warehouses, ...

HDFS: Assumptions

Data characteristics

1. **Large** data sets and files
2. **Streaming** data access
3. **Batch processing** rather than interactive users
4. **Write-once, read-many**

Fault tolerance

- HDFS cluster may consist of **thousands of nodes**
    - Each component has a non-trivial probability of failure
- There is **always** some component that is **non-functional**
    - i.e. failure is the norm rather than exception, and so
    - automatic failure **detection** and **recovery** is essential

HDFS: File System

Logical view: Linux-based hierarchical file system

- **Directories** and **files**
- Contents of files is divided into **blocks**
  - Usually 64 MB, **configurable** per file level
- User and group **permissions**
- Standard **operations** are provided
  - Create, remove, move, rename, copy, ...

Namespace

- Contains names of **all** **directories, files, and other metadata**
  - i.e. all data to capture the **whole logical view** of the file system
- Just a **single** namespace for the entire cluster

HDFS: Cluster Architecture

Master-slave architecture

- **Master: NameNode**
  - **Manages** the file system **namespace**
  - **Manages** file **blocks** (mapping of **logical to physical** blocks)
  - **Provides** the **user interface** for all the operations
    - Create, remove, move, rename, copy, ... file or directory
    - Open and close file
  - **Regulates** **access** to files by users
- **Slave: DataNode**
  - **Physically** **stores** file blocks within the underlying file system
  - **Serves** read/write **requests** from users
    - i.e. user data never flows through the NameNode
  - Has **no** **knowledge** about the file system

HDFS: Replication

Replication = maintaining of **multiple copies** of each file block

- **Increases** read **throughput**, increases fault **tolerance**
- **Replication factor** (number of copies)
  - **Configurable** per file level, usually 3

Replica placement

- **Critical** to reliability and performance
- **Rack-aware strategy**
  - Takes the physical **location** of nodes into account
  - Network **bandwidth** between the nodes on the same rack is greater than between the nodes in different racks
- **Common case** (replication factor 3):
  - **Two** replicas on two different nodes in a **local rack**
  - **Third** replica on a node in a **different rack**

HDFS: NameNode

How the NameNode Works?

- **FsImage** – data structure **describing** the **whole file system**
  - **Contains:** namespace + mapping of blocks + system properties
  - **Loaded** into the system memory (4 GB RAM is sufficient)
  - **Stored** in the local file system, periodical **checkpoints** created
- **EditLog** – transaction log for all the **metadata changes**
  - E.g. when a new file is created, replication factor is changed, ...
  - Stored in the local file system
- **Failures**
  - When the NameNode **starts up**
    1. FsImage and EditLog are **read** from the **disk**,
    2. **transactions** from EditLog are **applied**,
    3. new version of FsImage is **flushed** on the **disk**, and
    4. EditLog is **truncated**

HDFS: DataNode

How each DataNode Works?

- Stores physical file blocks
  - Each block (replica) is stored as a separate local file
  - **Heuristics** are used to place these files in local directories
- Periodically sends HeartBeat messages to the NameNode
- **Failures**
  - When a DataNode fails or in case of a network partition,
    - i.e. when the NameNode does not **receive** a HeartBeat message within a given time limit
    - the NameNode no longer sends read/write **requests** to this node,
    - **re-replication** might be **initiated**
  - When a DataNode starts up
    - Generates a **list** of all its blocks and sends a **BlockReport message** to the NameNode

HDFS: API

Available application interfaces

- Java API
  - Python access or C wrapper also available
- HTTP interface
  - Browsing the namespace and downloading the contents of files
- FS Shell – command line interface
  - Intended for the user interaction
  - Bash-inspired commands
  - E.g.:

```
hadoop fs -ls /
hadoop fs -mkdir /mydir
```

Hadoop MapReduce

Hadoop MapReduce

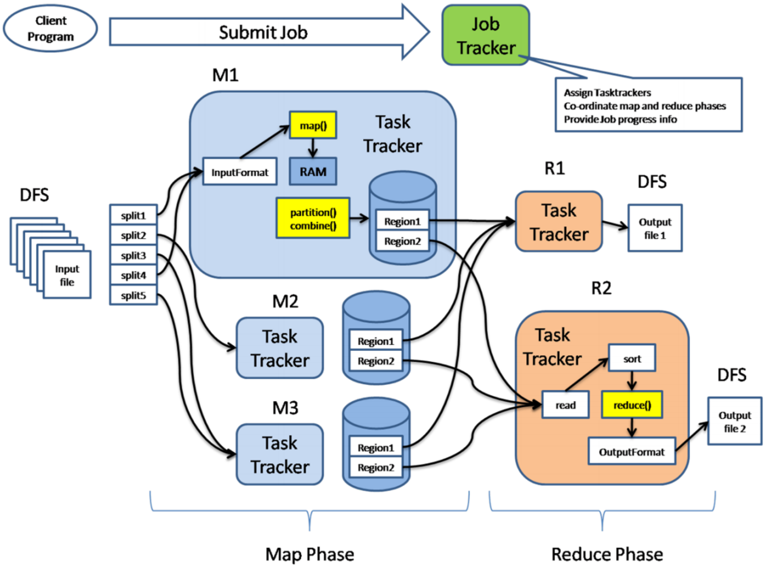
- MapReduce programming model implementation
- Requirements
  - **HDFS** – Input and output files for MapReduce jobs
  - **YARN** – Underlying distribution, coordination, monitoring and gathering of the results

Cluster Architecture

Master-slave architecture

- **Master: JobTracker**
  - **Provides** the **user interface** for MapReduce jobs
  - **Fetches** input file **data locations** from the NameNode
  - **Manages** the entire **execution** of jobs
    - Provides the **progress information**
  - **Schedules** individual **tasks** to **idle TaskTrackers**
    - Map, Reduce, ... tasks
    - Nodes **close** to the data are **preferred**
    - **Failed tasks** or **stragglers** can be **rescheduled**
- **Slave: TaskTracker**
  - **Accepts** tasks from the JobTracker
  - **Spawns** a separate JVM for each task execution
  - **Indicates** the available task slots via HearBeat messages

Execution Schema



Java Interface

Mapper class

- Implementation of the map function
- **Template parameters**
  - **KEYIN, VALUEIN** – types of input key-value pairs
  - **KEYOUT, VALUEOUT** – types of intermediate key-value pairs
- **Intermediate pairs** are **emitted** via context.write(k, v)

```java
class MyMapper extends Mapper<KEYIN, VALUEIN, KEYOUT, VALUEOUT> {
  @Override
  public void map(KEYIN key, VALUEIN value, Context context)
    throws IOException, InterruptedException
  {
    // Implementation
  }
}
```

Java Interface

Reducer class

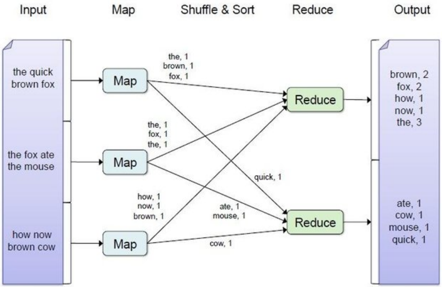
- Implementation of the reduce function
- **Template parameters**
  - **KEYIN, VALUEIN** – types of intermediate key-value pairs
  - **KEYOUT, VALUEOUT** – types of output key-value pairs
- **Output pairs** are **emitted** via context.write(k, v)

```java
class MyReducer extends Reducer<KEYIN, VALUEIN, KEYOUT, VALUEOUT> {
  @Override
  public void reduce(KEYIN key, Iterable<VALUEIN> values, Context context)
    throws IOException, InterruptedException
  {
    // Implementation
  }
}
```

Example

Word Frequency

- **Input:** Documents with words
  - Files located at /home/input HDFS directory
- **Map:** parses a document, emits (word, 1) pairs
- **Reduce:** computes and emits the **sum** of the associated values
- **Output:** overall number of **occurrences** for each word
  - Output will be written to /home/output



Example: Mapper Class

```java
public class WordCount {
  ...
  public static class MyMapper
    extends Mapper<Object, Text, Text, IntWritable>
  {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();
    @Override
    public void map(Object key, Text value, Context context)
      throws IOException, InterruptedException
    {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }
...
}
```

Example: Reducer Class

```
public class WordCount {
  ...
  public static class MyReducer
    extends Reducer<Text, IntWritable, Text, IntWritable>
  {
    private IntWritable result = new IntWritable();
    @Override
    public void reduce(Text key, Iterable<IntWritable> values,
      Context context) throws IOException, InterruptedException
    {
      int sum = 0;
      for (IntWritable val : values) {
        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }
  ...
}
```

Lecture Conclusion

MapReduce criticism

- MapReduce is a **step backwards**
  - Does not use **database schema**
  - Does not use **index structures**
  - Does not support **advanced query languages**
  - Does not support **transactions, integrity constraints, views, ...**
  - Does not support **data mining, business intelligence, ...**
- MapReduce is **not novel**
  - Ideas more than 20 years old and overcome
  - Message Passing Interface (MPI), Reduce-Scatter

The end of MapReduce?