B4M36DS2: **Database Systems 2**

http://www.ksi.mff.cuni.cz/~svoboda/courses/2016-1-B4M36DS2/

Lecture 2

MapReduce, Apache Hadoop

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Lecture Outline

MapReduce

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

Apache Hadoop

- HDFS – *Hadoop Distributed File System*
- MapReduce

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 us to work at a (much) **higher level of abstraction**
- The point is
  <u>how the intended user **thinks** in order to solve their tasks</u>
  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++, …)

Programming Models

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 <u>disjoint partitions of data</u>
- Implicit parallelism

MapReduce Framework

What is MapReduce?

- **Programming model + implementation**
- Developed by Google in 2008

Google: 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

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**
- **Computation tasks executed in parallel across the nodes**

Classification

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

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 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

And that's all!

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*: a key-value pair
- *Output*: **a set of intermediate key-value pairs**
  - Usually from a different domain
  - Keys do not have to be unique
- $(k_1, v_1) \rightarrow \texttt{list}(k_2, v_2)$

Reduce function

- *Input*: **an intermediate key + a set of values** for this key
- *Output*: **a possibly smaller set of values** for this key
  - From the same domain
- $(k_2, \texttt{list}(v_2)) \rightarrow (k_2, \texttt{list}(v_2))$

Example: Word Frequency

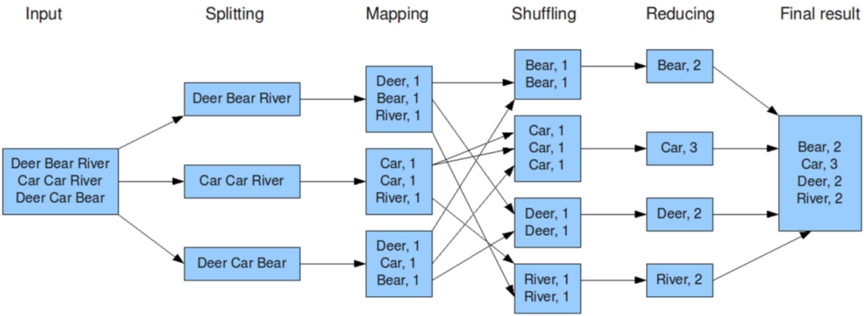
Implementation

```
/**
 * Map function
 * @param key   Document name
 * @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 associated with the word
 */
reduce(String key, Iterator values) {
  int result = 0;
  foreach v in values: result += v;
  emit(key, result);
}
```

Example: Word Frequency

Execution Phases



Execution: Phases

Splitting

- Input key-value pairs (documents) are parsed and prepared

Mapping

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

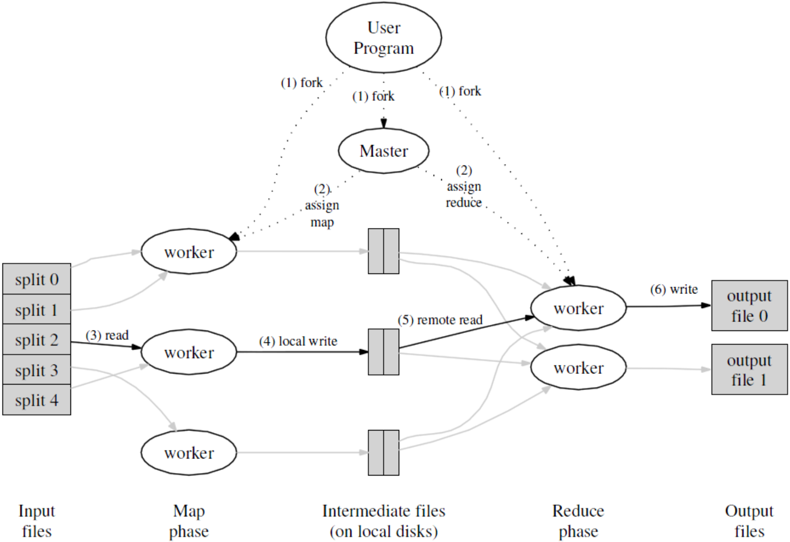
Shuffling

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

Reducing

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

Execution: Schema



Execution: Components

Input reader

- Reads data from a stable storage (e.g. a distributed file system)
- Splits the data into appropriate size blocks (splits)
- Parses these blocks and **prepares input key-value pairs**

Map function

Partition function

- Determines Reduce task for an intermediate key-value pair
  - E.g. hash of the key modulo the overall number of reducers

Compare function

- Compares two intermediate keys, used during the shuffling

Reduce function

Output writer

- Writes the output of the Reduce function to stable storage

Additional Aspects

Combine function

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

Additional Aspects

Counters

- Allow to track the progress of a MapReduce job in real time
  - **Predefined counters**
    - E.g. numbers of launched 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

Additional 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

Additional Aspects

Stragglers

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

Additional Aspects

Task granularity

- Intended **numbers of Map and Reduce tasks**
- Practical recommendation (Google)
  - **Map tasks**
    - Choose the number so that each individual Map task has roughly 16 – 64 MB of input data
  - **Reduce tasks**
    - Small multiple of the number of worker nodes we expect to use
    - Note also that the **output of each Reduce task ends up in a separate output file**

Further 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

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

Further Examples

Distributed sort

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

Reverse web-link graph

- *Input*: web pages with `<a href="…">…</a>` tags
- *Map*: emits (target URL, this URL) pairs
- *Reduce*: emits the associated source URLs unchanged
- *Output*: list of URLs of web pages targeting a given one

Further 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: 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

Apache Hadoop

Open-source software framework

- http://hadoop.apache.org/
- **Distributed storage and distributed processing** of very large data sets on clusters built from commodity hardware
  - Implements a **distributed file system**
  - Implements **MapReduce**
- 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

- Hadoop **Common**
  - Common utilities and support for other modules
- Hadoop **Distributed File System** (HDFS)
  - High-throughput distributed file system
- Hadoop **Yet Another Resource Negotiator** (YARN)
  - Cluster resource management
  - Job scheduling framework
- 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

- **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
- **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
- **Spotify** – content generation, data aggregation, reporting, analysis:
  1650 nodes, 43000 cores, 70 TB RAM, 65 PB, 20000 daily jobs
- **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

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

Fault tolerance

- HDFS cluster may consist of thousands of nodes
  - Each component has a non-trivial probability of failure
- $\Rightarrow$ <u>there is always some component that is non-functional</u>
  - 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**
  - **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
  - **Manages file blocks** (mapping of logical to physical blocks)
- 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 those 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**
    - FsImage and EditLog are read from the disk, transactions from EditLog are applied, new version of FsImage is flushed on the disk, 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 **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**

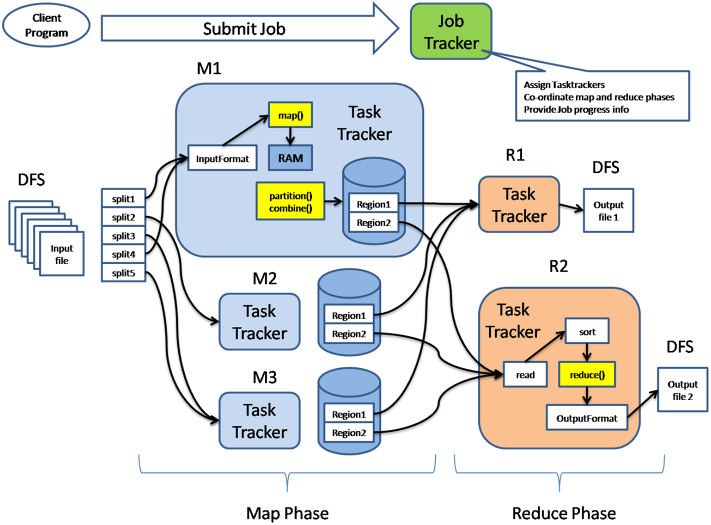
- MapReduce programming model implementation
- Requirements
  - **HDFS**
    - Input and output files for MapReduce jobs
  - **YARN**
    - Underlying distribution, coordination, monitoring and gathering of the results

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)`

```
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)`

```
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 `/user/martin/input` HDFS directory
- *Map*: parses a document, emits $(\text{word}, 1)$ pairs
- *Reduce*: computes and emits the sum of the associated values
- *Output*: overall number of occurrences of a given word
  - Output will be written to `/user/martin/output`

MapReduce **job execution**

```
hadoop jar wc.jar WordCount /user/martin/input /user/martin/output
```

Example: Mapper Class

```
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);
    }
  }
  …
}
```

Conslusion

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?