CS535 BIG DATA

## PART 0. INTRODUCTION
## 3. DATA MODEL FOR BIG DATA
## : APACHE THRIFT

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## FAQs

- Programming Assignment 1
  - Due Sept. 28
  - Submission via Canvas
  - Please check the course Web Page at least twice a week

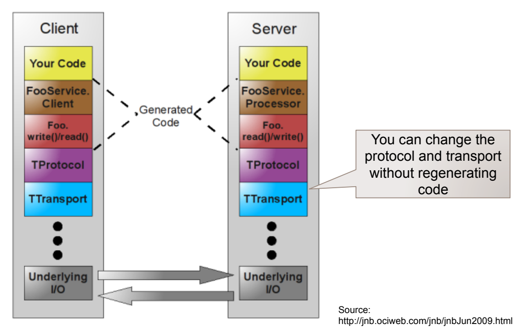


## Today's topics

- Apache Thrift continued
- Introduction to MapReduce



## Thrift Architecture




Source: http://jnb.ociweb.com/jnb/jnbJun2009.html



## Protocol



## Protocols (1/2)

- Describes "what" is transmitted

- Thrift supports both text and binary protocols
  - The binary protocol outperforms text protocol
  - The text protocol may be useful (such as in debugging)

- `TBinaryProtocol`
  - A straight-forward binary format encoding numeric values as binary, rather than converting to text.

- `TCompactProtocol`
  - Very efficient, dense encoding of data

## Protocols (1/2)

- `TDenseProtocol`
  - Similar to `TCompactProtocol` but strips off the meta information from what is transmitted, and adds it back in at the receiver.
- `TJSONProtocol`
  - Uses JSON for encoding of data.
- `TSimpleJSONProtocol`
  - A write-only protocol using JSON. It cannot be parsed by Thrift. Suitable for parsing by scripting languages
- `TDebugProtocol`
  - Uses a human-readable text format to aid in debugging.



## TCompactProtocol

- The `TCompactProtocol` is the most-efficient method in the Java implementation of Thrift
  - Writes numeric tags for each piece of data
  - The recipient is expected to properly match these tags with the data
  - If the data is not present, there simply is no tag/data pair



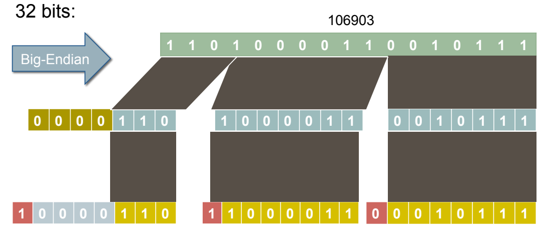

## TCompactProtocol (1/2)

- For integers, the TCompactProtocol performs compression Variable-Length Quantity (VLQ) encoding
- VLQ uses 7 of 8 bits out of each byte for information
  - the 8th bit used as a continuation bit



## TCompactProtocol (2/2)

- Decimal value 106903 (0x1A197) saving 1 byte if it was stored in 32 bits:




VLQ's worst-case encoding
For a 32-bit int, the worst case is 5 bytes
For 64-bit ints, the worst case is 10 bytes



## Versioning



## Versioning

- **Applications** evolve over time
  - You added an extra field to your message format
- The system **must be able to support reading of old data** from log files
  - Process requests from out-of-date clients to new servers and vice versa

## Versioning Field Identifiers

- Any new fields should be optional
  - Any messages serialized by code using the “old” message format **can be parsed** by the new code
    - Without any missing required fields (Parsing error)
  - Messages created by new code can be parsed by old code
    - Old binary will ignore the new field when parsing
    - Unknown fields are not discarded: it will be serialized along with other fields
- Non-required fields can be removed
- Changing a default value is allowed
- Mark Slee, Aditya Agarwal and Marc Kwiatkowski, Thrift: Scalable Cross-Language Services Implementation, https://thrift.apache.org/static/files/thrift-20070401.pdf

CS535 BIG DATA

PART 1. BATCH COMPUTING MODELS FOR BIG DATA ANALYTICS

## 1. DISTRIBUTED MODEL FOR SCALABLE BATCH COMPUTING - MAPREDUCE

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## This material is built based on

- Jeffrey Dean and Sanjay Ghemawat, "MapReduce:Simplified Data Processing on Large Clusters" In Proceeding OSDI'04 Proceedings of the 6th conference on Symposium on Opearting Systems Design & Implementation - Vol. 6
- Hadoop: The definitive Guide, Tom White, O’Reilly, 3rd Edition, 2014
- MapReduce Design Patterns, Donald Miner and Adam Shook, O’Reilly, 2013
- Anand Rajaraman, Jure Leskovec, and Jeffrey Ullman, “Mining of Massive Datasets”, Cambridge University Press, 2012 -- Chapter 2



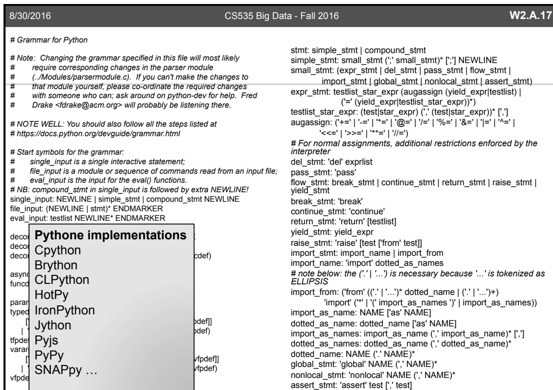
## Why MapReduce?



## What is MapReduce?

- MapReduce is inspired by the concepts of *map* and *reduce* in Lisp.






Programming language specification: Python 3.5.2

## What is MapReduce?

- Developed within Google as a mechanism for processing large amounts of raw data.
  - Crawled documents or web request logs
  - Distributes these data across thousands of machines
  - Same computations are performed on each CPU with a different portion of the dataset



## Why MapReduce?

- MapReduce provides an abstraction that allows engineers to perform simple computations while hiding the details of:
  - Parallelization
  - Data distribution
  - Load balancing
  - Fault tolerance



## Example

- Climate data from National Climatic Data Center (NCDC)

```
0057
332130 # USAF weather station identifier
99999 # WBAN weather station identifier
19500101 # observation date
0300 # observation time 4
+ 51317 # latitude (degrees x 1000)
+ 028783 # longitude (degrees x 1000)
FM-12
+ 0171 # elevation (meters)
99999
V020
320 # wind direction (degrees)
1 # quality code
```



## The first entries for 1990

```
% ls raw/ 1990 | head
010010-99999-1990.gz
010014-99999-1990.gz
010015-99999-1990.gz
010016-99999-1990.gz
010017-99999-1990.gz
010030-99999-1990.gz
010040-99999-1990.gz
010080-99999-1990.gz
010100-99999-1990.gz
010150-99999-1990.gz
```



## Analyzing the data with Unix Tools (1/2)

- A program for finding the **maximum recorded temperature by year** from NCDC weather records
  - e.g. Weather change for a century

```
#!/ usr/ bin/ env bash
for year in all/*
do
 echo -ne ` basename $ year .gz `"\ t”
 gunzip -c $ year | \
   awk '{
      temp = substr( $ 0, 88, 5) + 0;
      q = substr( $ 0, 93, 1);
      if (temp != 9999 && q ~ /[01459]/ && temp > max)
          max = temp
      }
      END { print max }'
Done
```



## Analyzing the data with Unix Tools (2/2)

- The script loops through the compressed year files
  - Printing the year
  - Processing each file using `awk`
    - Extracts two fields
    - Air temperature and the quality code
    - Check if it is greater than the maximum value seen so far

```
% ./ max_temperature.sh
1901 317
1902 244
1903 289
1904 256
1905 283
…
```

## Results?

- The complete run for the century took 42 minutes
- To speed up the processing
  - We need to run parts of the program in parallel
  - Process different years in different processes
  - What will be the problems?



## Challenges

- **Dividing the work** into equal-size pieces
  - Data size per year?
- **Combining the results** from independent processes
  - Combining results and sorting by year?



## Map and Reduce

- MapReduce works by breaking the processing into two phases
  - The map phase
  - The reduce phase
- Each phase has key-value pairs as input and output
- Programmers should specify
  - Types of input/output key-values
  - The map function
  - The reduce function



## Visualizing the way MapReduce works (1/4)

Sample lines of input data

```
0067011990999991950051507004... 9999999N9 + 00001 +99999999999...
0043011990999991950051512004... 9999999N9 + 00221 +99999999999...
0043011990999991950051518004... 9999999N9-00111 +99999999999...
0043012650999991949032412004... 0500001N9 + 01111 +99999999999...
0043012650999991949032418004... 0500001N9 + 00781 +99999999999…
```

These lines are presented to the map function as key-value pairs

```
(0, 0067011990999991950051507004...9999999N9 + 00001+
99999999999...)
(106, 0043011990999991950051512004...9999999N9 + 00221+
99999999999...)
(212, 0043011990999991950051518004...9999999N9-0011 1 +
99999999999...)
```

The keys are the line offsets within the file



## Visualizing the way MapReduce works (2/4)

The **map function** extracts **the year and the air temperature** and emits them as its output

```
(1950, 0)
(1950, 22)
(1950, − 11)
(1949, 111)
(1949, 78)
```

This output key-value pairs will be **sorted and grouped by key**. Our reduce function will see the following input:

```
(1949, [111, 78])
(1950, [0, 22, −11])
```

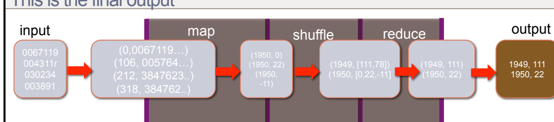


## Visualizing the way MapReduce works (3/4)

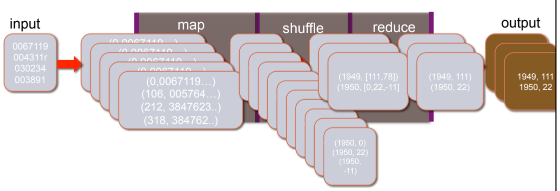
Reduce function iterates through the list and picks the maximum reading

```
(1949, 111)
(1950, 22)
```

This is the final output



## Visualizing the way MapReduce works (4/4)






## Map and Reduce



## Map function

- Takes an input pair
- **Produces a set of intermediate key/value pairs**
- The MapReduce library groups together all intermediate values associated with the same intermediate key *i* and passes them to the reduce function



## Reduce function

- **Accepts an intermediate key** *i* and a set of values for that key
- **Merges** together these values
  - Forms a possibly smaller **set** of values



## Example: counting words

- Count the number of occurrences of each word in a large collection of documents:

```
map(String key, String value):
// key: document name
// value: document contents
for each word w in value:
    EmitIntermediate(w,"1");


reduce(String key, Iterator values):
//key: a word
//values: a list of counts
int result = 0;
for each v in values:
      result += ParseInt(v)
Emit(AsString(result));
```

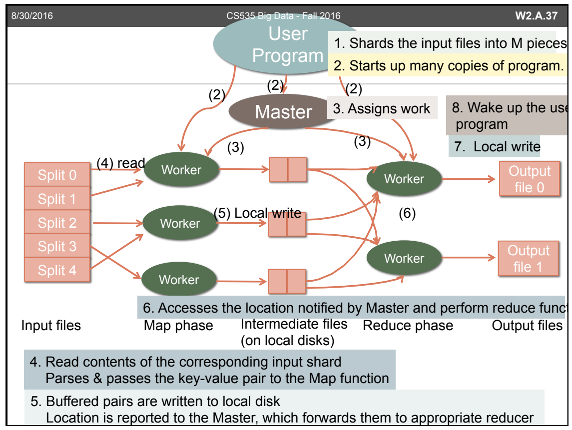


## Comparison with other systems

- MPI vs. MapReduce
  - MapReduce tries to collocate the data with the compute node
  - Data access is fast
    - Data is local!
- Volunteer computing vs. MapReduce
  - SETI@home
    - Uses donated (volunteered) CPU time

# MapReduce Data Flow








# Job execution framework

- `mapred.job.tracker`
  - If the configuration property is set to `local`
    - Local job runner is used
    - Whole job will be in a single JVM
    - Designed for testing and running with small datasets
  - Using `classic`
    - For the classic MapReduce framework (MapReduce 1)
  - Using `yarn`
    - For the YARN framework

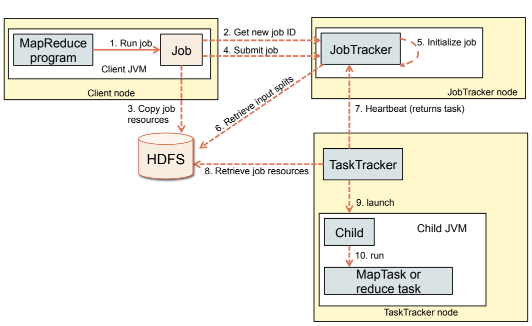


# Job submission

- Single method call
  - `submit()` on a `Job` object
    - You can also call `waitForCompletion()`
- Creates an internal `JobSubmitter` instance
  - Calls `submitJobInternal()` on it
- `waitForCompletion()`
  - Polls the job's progress once per second
  - Reports the progress to the console if it has changed since the last report
- Job completes successfully
  - The job counters are displayed
  - Otherwise, the error is logged to the console



# MapReduce job in the Classic framework






# Job submission process in Classic framework

- Asks the jobtracker for a new jobID
  - Step 2
- Checks the output specification of the job
- Computes the input splits for the job
- Copies the resources to the jobtracker's filesystem in a directory named after the jobID
  - The job JAR file, the configuration file, and the computed input splits
- Tells the jobtracker that the job is ready for execution by calling `sumitJob()` on `JobTracker`
  - Step 4

## Job Initialization in the Classic mode

- JobTracker puts the job into an internal queue
  - Creating an object to represent the job being run
  - Bookkeeping information to keep track of the status and progress of its tasks
- Creating the list of tasks
  - The job scheduler retrieves the input splits
  - The job scheduler creates a map task for each split
  - The number of reduce tasks to create
    - mapred.reduce.tasks property in the Job
      - setNumReduceTasks()
  - A job setup task and a job cleanup task are created



## Task assignment

- Jobtracker select a job to run
  - Default algorithm
    - Based on the priority list of jobs
- Tasktrackers have a fixed number of slots for map tasks and reduce tasks
  - These are set independently
  - These are selected based on the number of cores and the memory
- The default scheduler fills empty map task slots first
  - Before it fills the reduce task slots
  - Scheduling the reduce task does not need to consider data locality
- Tasktrackers run a simple loop that periodically sends heartbeat method calls to the jobtracker



## Task execution

- `Tasktracker`
  - Copies the job Jar to the tasktracker's file system
    - Any files needed from the distributed cache to the local file system
  - Creates a local working directory
  - Creates instance of `TaskRunner`
- `TaskRunner`
  - Launches a new Java Virtual Machine to run each task
    - Any failed map or reduce does not affect the tasktracker



## Streaming and pipes

- Runs special map and reduce tasks
  - To launch the user supplied executable
  - To communicate with it
- Streaming task communicates with the process using standard input and output streams
- Pipes task listens on a socket and passes the C++ process a port number in its environment
  - On startup, the C++ process establish a persistent socket connection back to the parent Java Pipes task



## Progress and status updates [1/3]

- A Job and each of its tasks have a status
  - State of the job or task
    - E.g. running, successfully complete, failed
  - The progress of maps and reduces
  - The values of the job's counters
  - A status message or description
- Progress of a task
  - The proportion of the task completed
  - Map task
    - The proportion of the input that has been processed
  - Reduce task
    - Divides the total progress into 3 parts (copy/sort/reduce)
    - If the task has run the reducer on half its input
      - 1/3 (copy) + 1/3 (sort) + a half of 1/3(reduce phase) = 5/6



## Progress and status updates [2/3]

- Tasks
  - have a set of counters
  - Count various events at the task run
  - E.g. the number of map output records written
  - If a task reports progress
    - it sets a flag to indicate that the status change should be sent to the tasktracker
      - Checked every 3 seconds
- Tasktracker
  - Tasks notify the current task status to the tasktracker
    - if the flag is set
  - Tasktracker sends heartbeats to the jobtracker every 5 seconds (minimum)

## Progress and status updates [2/3]

- Jobtracker
  - Combines updates to produce a global view
- Job
  - Receives the latest status by polling the jobtracker every second
  - Prints job statistics and counters to the console



## YARN (MapReduce 2)

- To provide the scalability to MapReduce
  - Splitting responsibility of the jobtracker
    - Scheduling
    - Task progress monitoring
- MapReduce is one type of YARN application