Hybrid Map Task Scheduling for GPU-based Heterogeneous Clusters

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The data generated by human activities is rapidly increasing

- Massive data processing
  - Various scientific computation (biology, astronomy, …)
- MapReduce
  - Programming model for massive data processing
  - Scalable parallel data processing
- GPGPU
  - Better performance compared to CPU

  → Emerging of GPU-based Hybrid Supercomputer and Cloud

  ex) TSUBAME 2.0 : NVIDIA Fermi "Tesla M2050" x3 in a node

MapReduce acceleration by using GPUs

Problems of MapReduce on CPU-GPU Hybrid Clusters

- Scheduling Map tasks onto CPUs and GPUs efficiently is difficult
- Dependence on computational resource
  - # of CPU cores, GPUs, amount of memory, memory bandwidth, I/O bandwidth to storage
- Dependence on applications
  - GPU computation characteristic
    - Pros. Peak performance, memory bandwidth
    - Cons. Complex instructions

Hybrid Scheduling with CPUs and GPUs to make use of each excellence → Exploit computing resources

Goal and Achievement

- Goal
  - Acceleration of MapReduce in hybrid environment with CPUs and GPUs
- Achievement
  - Hybrid Map Task execution
    - Implemented on Hadoop, MapReduce OSS
  - Map Task Scheduling technique
    - Minimize total job execution time
  - Evaluation by K-means
    - Job execution time: 1.93 times faster by using multiple GPUs and proposed scheduling technique than CPU-only at 64 nodes.

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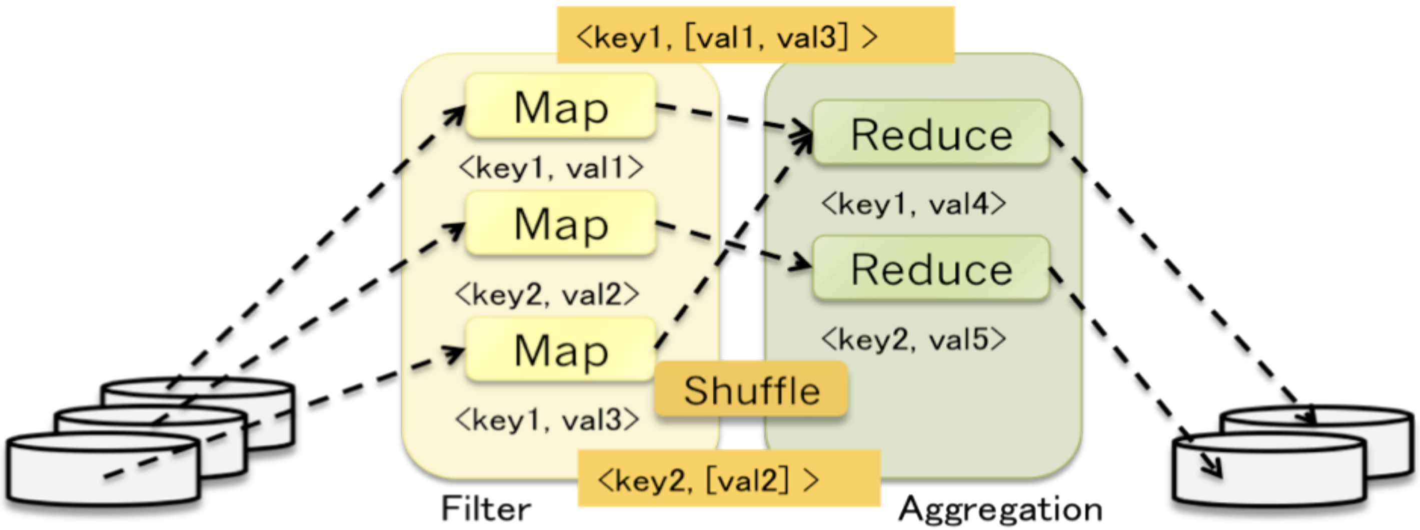
MapReduce

- Data analysis, Machine learning applications
- Implementations
  - Hadoop: OSS of HDFS, MapReduce, HBase
  - Mars: framework for GPU

  → We implemented in Hadoop, widely used in many companies and institutes



GPGPU

- Graphic processors are used as SIMD
- Higher peak performance than CPUs
- Integrated developing environment
  - NVIDIA: CUDA
    - High level abstraction in a SIMD-style
    - Specific to NVIDIA GPUs
  - AMD: OpenCL
    - An open standard that can be used to program CPUs, GPUs from different vendors

→ We use CUDA, which provides C- and C++-based programming environment for NVIDIA GPUs

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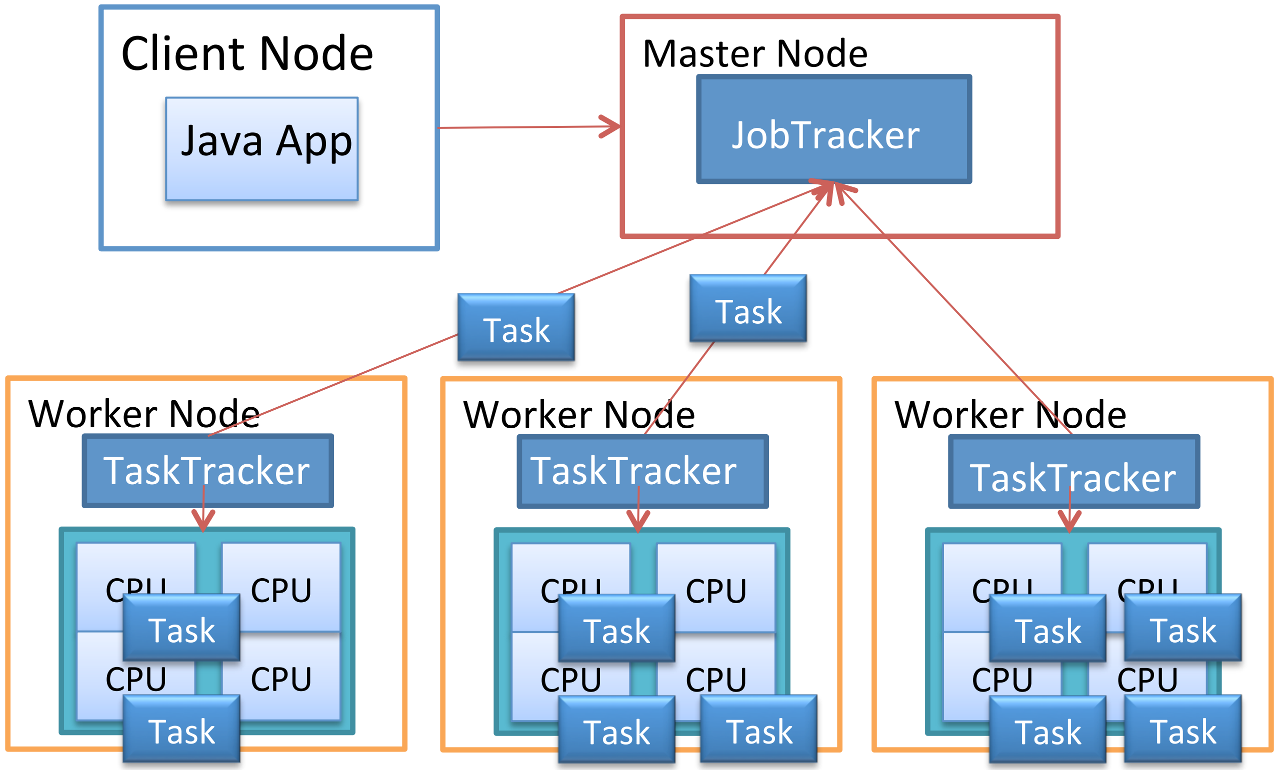
Structure of Hadoop

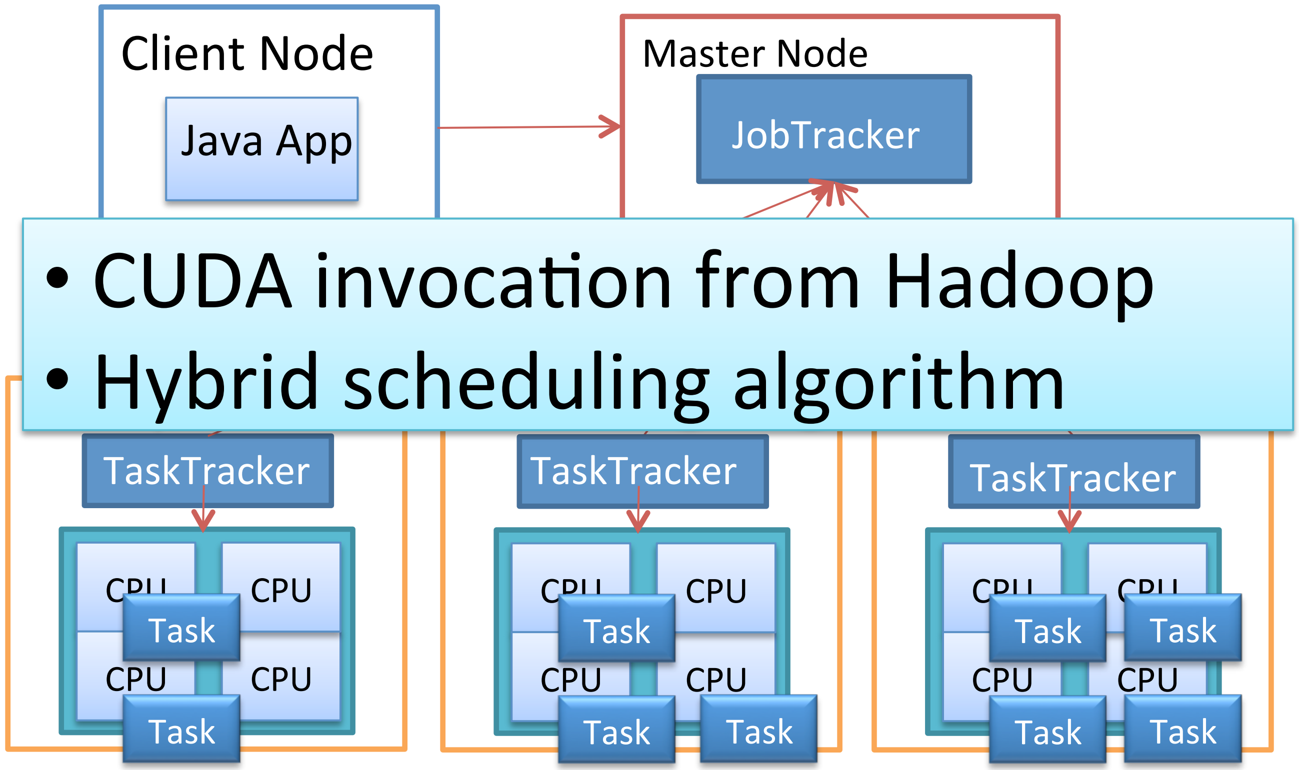
- Master/Worker model
  - Master: JobTracker
    - Manages submitted jobs
  - Worker: TaskTrackers
    - Execute map and reduce tasks



Idea: Hybrid Map task scheduling onto CPUs and GPUs

- Automatic scheduling onto CPUs and GPUs
  - A runtime environment, Computing resources
  - Application characteristics

→ Minimize the job execution time



- CUDA invocation from Hadoop
- Hybrid scheduling algorithm

CUDA invocation strategy from Hadoop

- Translation of a Java program to a CUDA code
  - Hadoop → Java (Middleware, Application)
  - CUDA → C or C++ library
- How to translate CUDA in Hadoop environment
  - Hadoop Streaming: Standard I/O
  - Hadoop Pipes: C++ library, Socket connection,
  - JNI, JNI-based CUDA wrapper (JCUDA)

  → We use Hadoop Pipes for our proposed technique
    - MapReduce applications/CUDA kernel → written in C++

CUDA invocation strategy from Hadoop (cont'd)

- Management of Map tasks, idle slots
  - Which slot each Map task should run on
  - Which CPU/GPU slots are idle
- Map task contention to GPU
  - When a TaskTracker node has Multiple GPUs
  - Management of which Map tasks run on which GPU devices
    - We set the GPU device number by cudaSetDevice() at the invocation of a GPU binary program

Hybrid scheduling strategy

- Minimization of total job execution time
  - Allocation of Map tasks by performance ratio of CPU and GPU map task execution (acceleration factor)
- Dynamic monitoring
  - Execution on both CPU and GPU map tasks simultaneously to collect profiles
  - Getting profiles of finished Map tasks on CPUs and GPUs periodically (e.g. execution time)
  - Calculation of the acceleration factor
  - Monitoring of the Job progress

Scheduling algorithm

- Goal
  - Minimize the time all the Map tasks are assigned
  - Calculate # of Map tasks to assign to CPUs, GPUs
- Acceleration factor

$$\alpha = \frac{mean\ map\ task\ execution\ time\ on\ CPU\ cores}{mean\ map\ task\ execution\ time\ on\ GPU\ devices}$$

- Scheduling algorithm

Minimize

$$f(x, y) \quad (1)$$

Subject to

$$f(x, y) = \max\{\frac{x}{n} \cdot \alpha \cdot t, \frac{y}{m} \cdot t\} \quad (2)$$

$$x + y = N \quad (3)$$

$$x, y \geq 0 \quad (4)$$

Input

•CPU cores: *n*, GPUs: *m*

Monitoring

•Remaining Maps tasks: *N*

•Runtime of 1 GPU task: *t*

•Acceleration factor: *α*

Output

•Total Map tasks to run on CPUs: *x*, on GPUs: *y*

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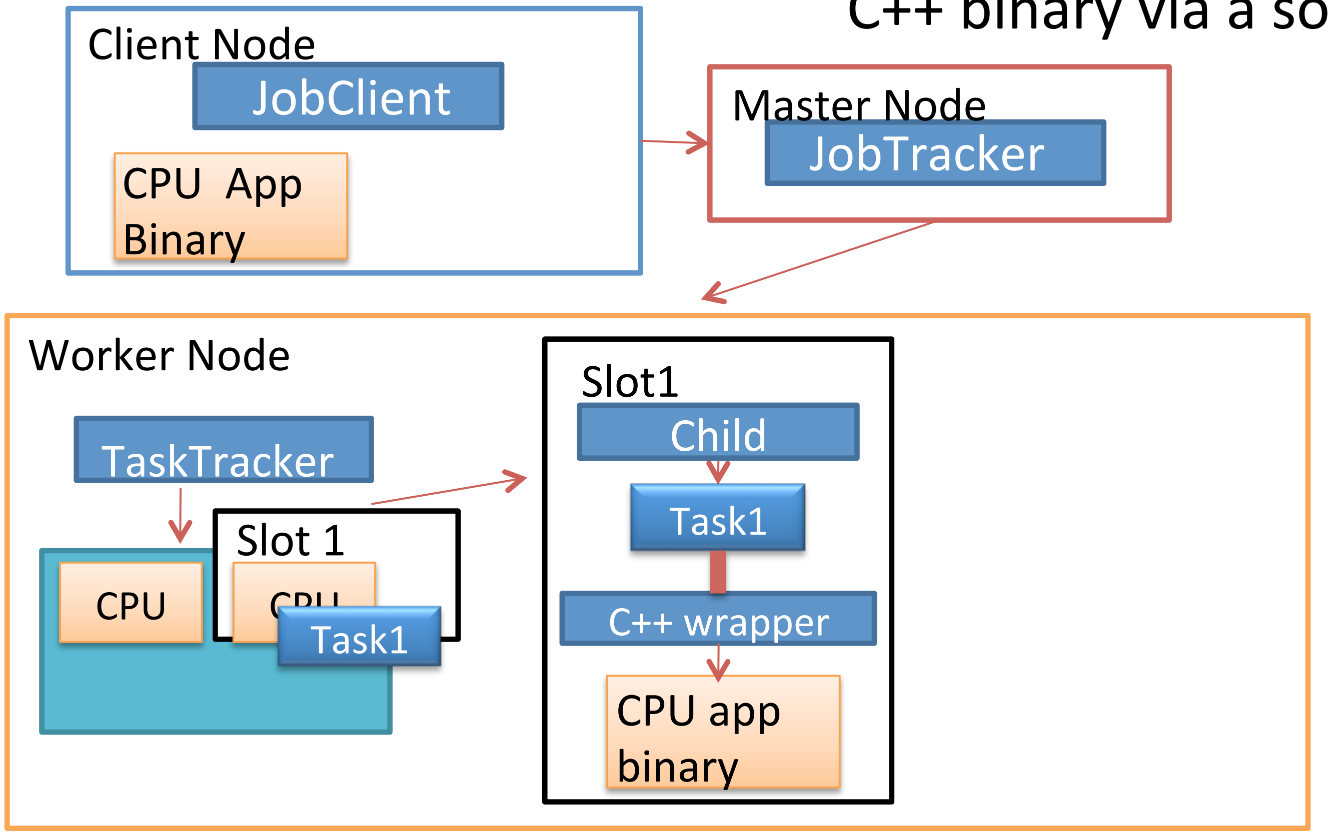
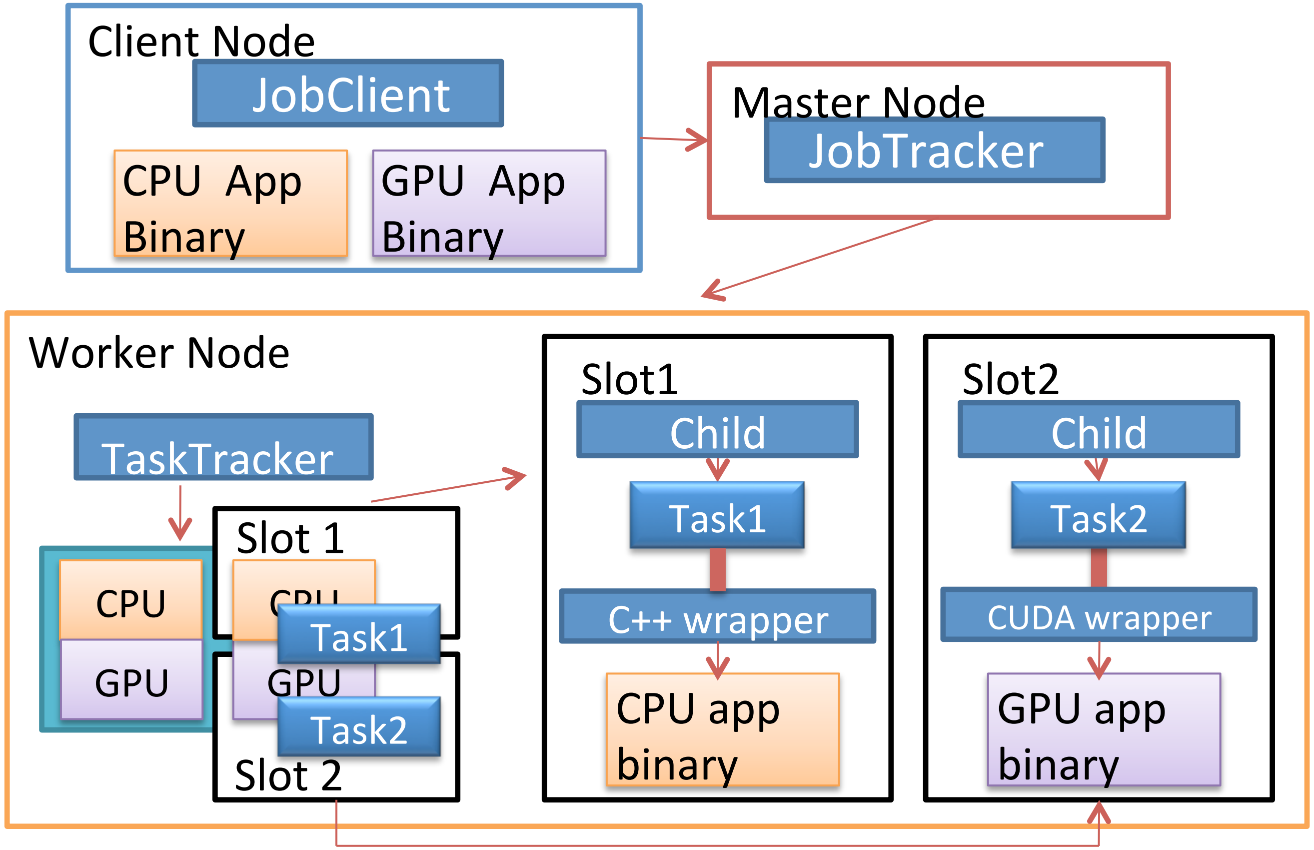
How Hadoop Pipes works

- Users
  - write map/reduce functions (with C++ wrapper library)
  - specify compiled binary, and run the job
- Execution overflow
  - A Child JVM invokes map or reduce tasks on a TaskTracker
  - A C++ wrapper process send/receive key-value pairs to/from C++ binary via a socket

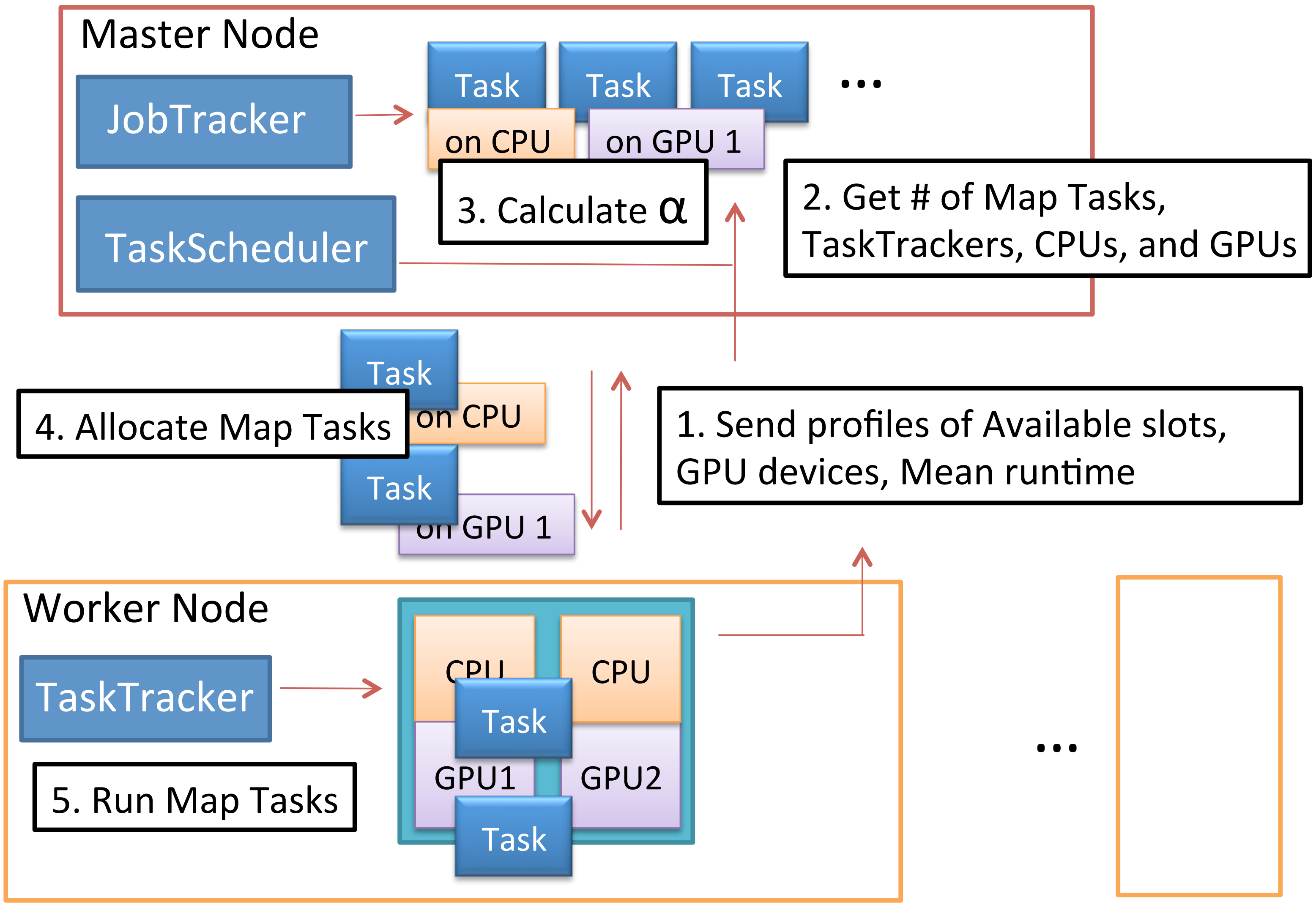


Hybrid execution by using Hadoop Pipes

- Specification of CPU/GPU binary when a job is launched
- TaskTrackers monitor the behavior of running map tasks
  - The elapsed time of a map task
  - The used CPU cores and GPU devices



The map task scheduling workflow



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Experiments setting

- Measurement of the Job execution time on Hadoop-based environment
  - Comparison between
    - CPU-only and CPU + GPU hybrid execution
    - Hadoop original and proposed scheduling
- K-means application
  - Running Map tasks with C++ binary and CUDA binary
  - 20GB of files with 4000 sets of 262,144 floating points and 128 clusters
    - Map: executes K-means for each file
    - Reduce: collects the result of each K-means

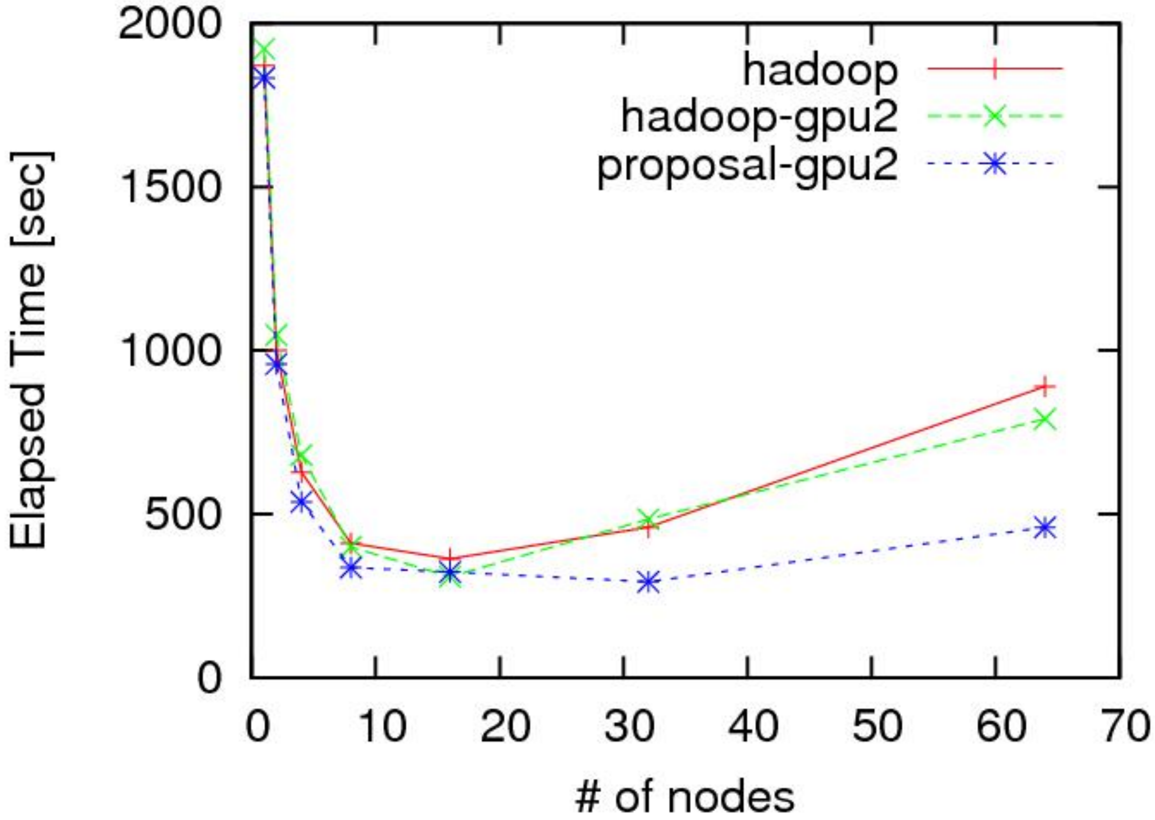
Experimental environment

- TSUBAME1.2
  - We use up to 64 nodes (1024 CPU cores and 128 GPU devices)
  - Lustre file system as DFS (stripes: 4, Chunk size: 32 MB)
    - I/O performance: Write 180MB/s, Read 610MB/s (with 32 MB file)
  - Hadoop 0.20.1, Java 1.6.0, CUDA 2.3

Specification of a single compute node

CPU	Dual Core AMD Opteron 880 (2.4 GHz)
# of cores	16
Main MEM	32GB
GPU	NVIDIA Tesla S1070 (T10-based card $\times$ 4) shared by 2 compute nodes
# of cards	2
# of cores per card	240 cores (1.29 - 1.44 GHz)
Global MEM per card	4GB
Interconnect	SDR Infiniband $\times$ 2
PCI-Express Bandwidth	2GB/s
OS	Linux 2.6.16

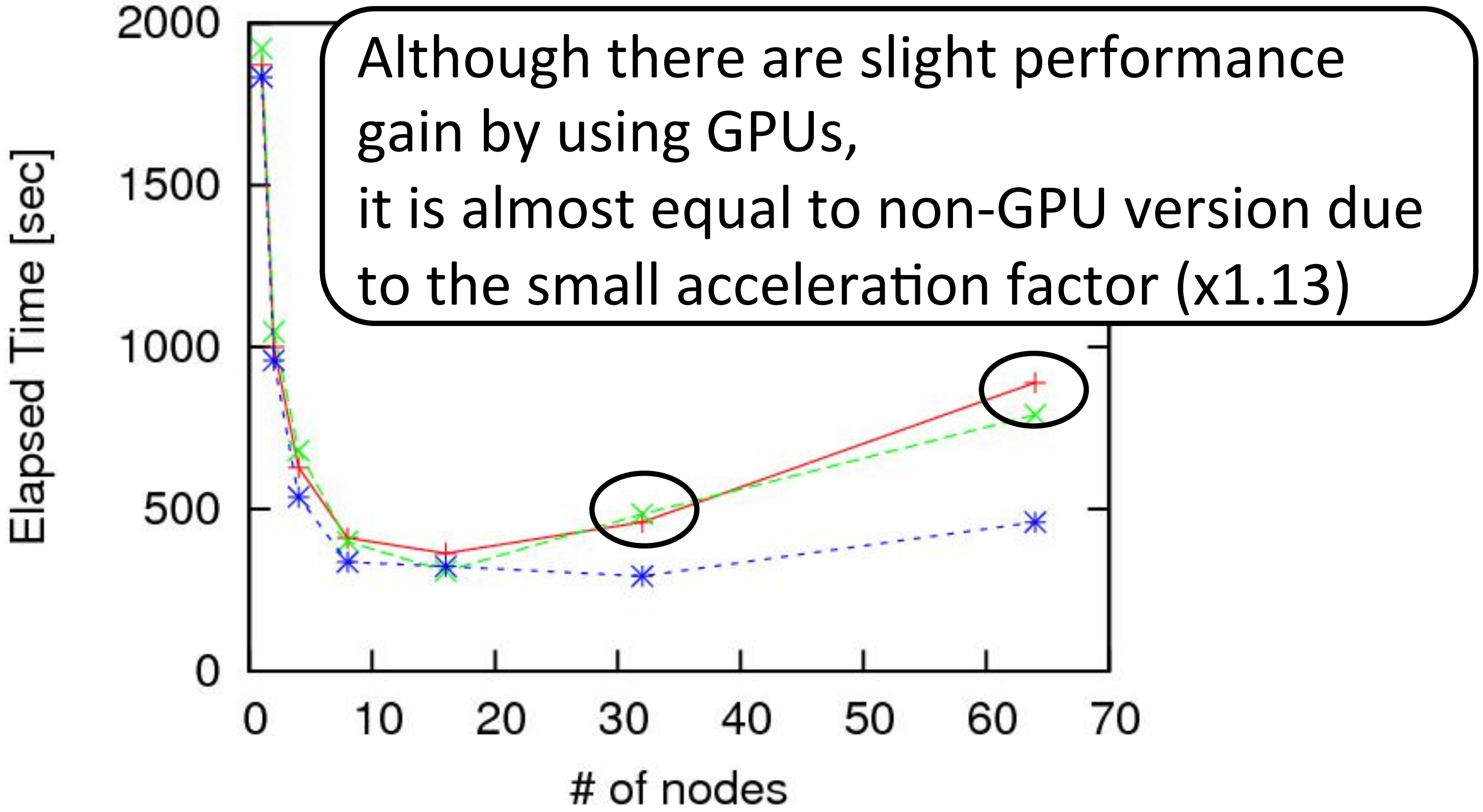
Comparison of Job execution time



Total MapReduce job execution time

-hadoop: Hadoop original scheduling
-hadoop-gpu2: Hadoop original scheduling with 2 GPU devices / node
-proposal-gpu2: Proposed scheduling with 2 GPU devices /node

Comparison of Job execution time



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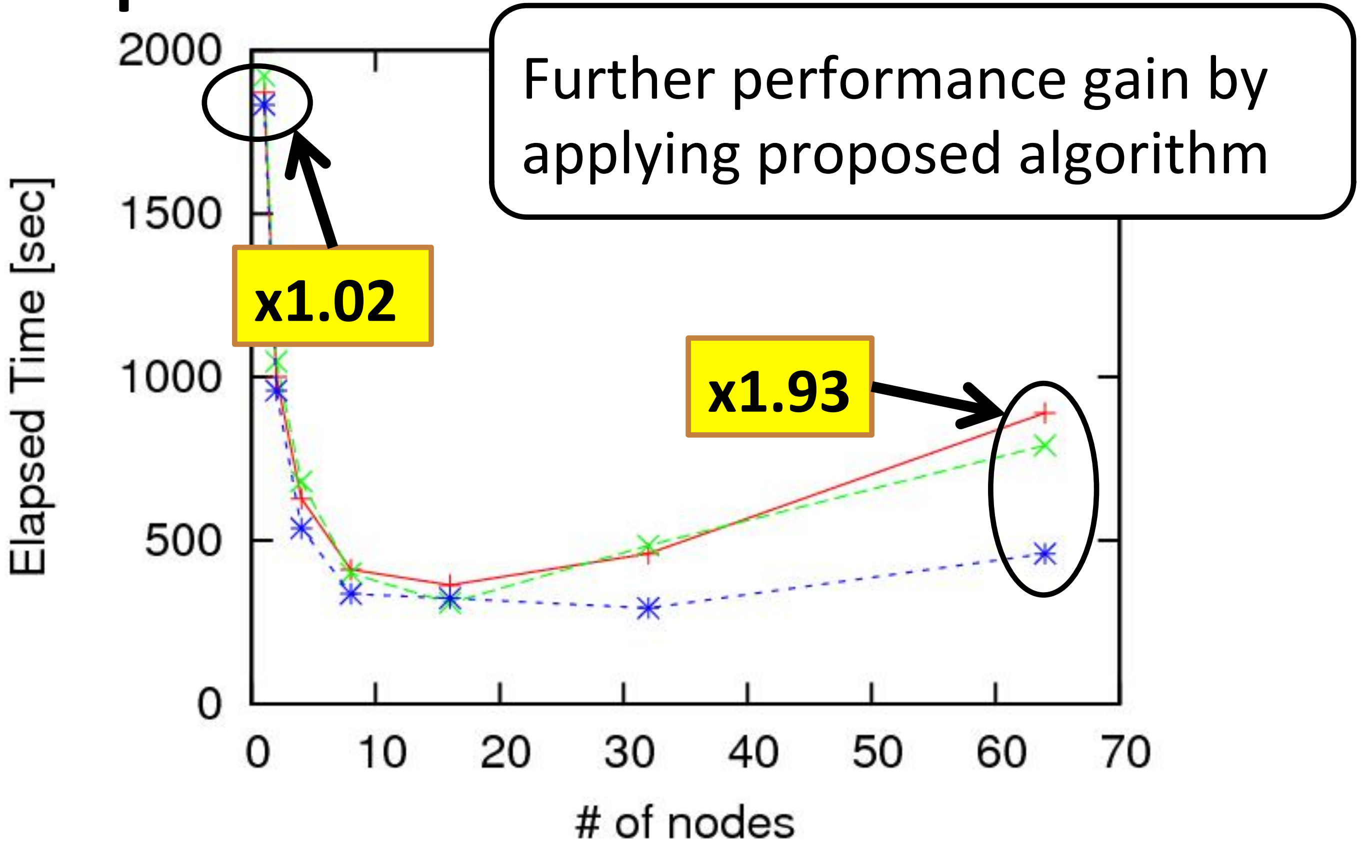

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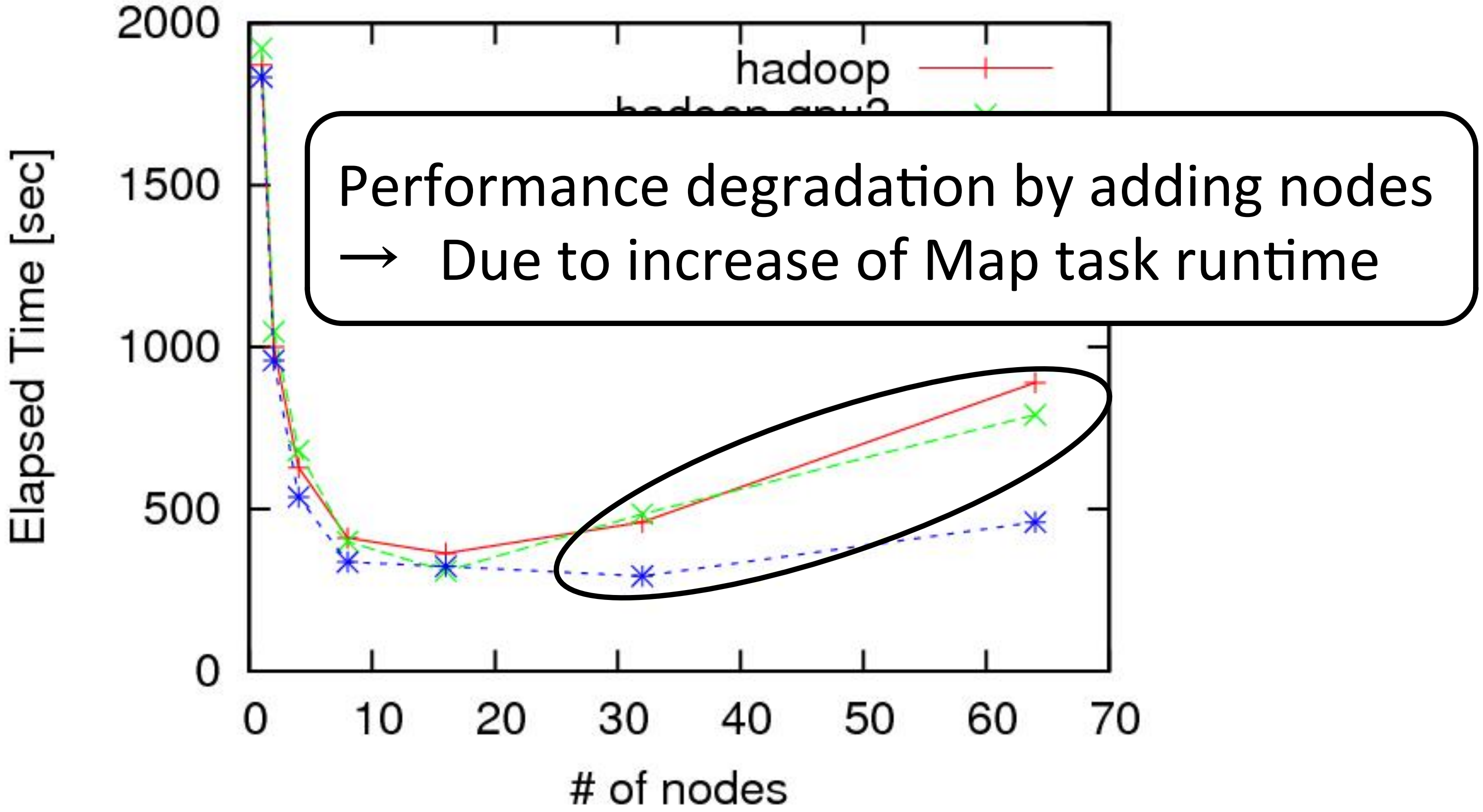

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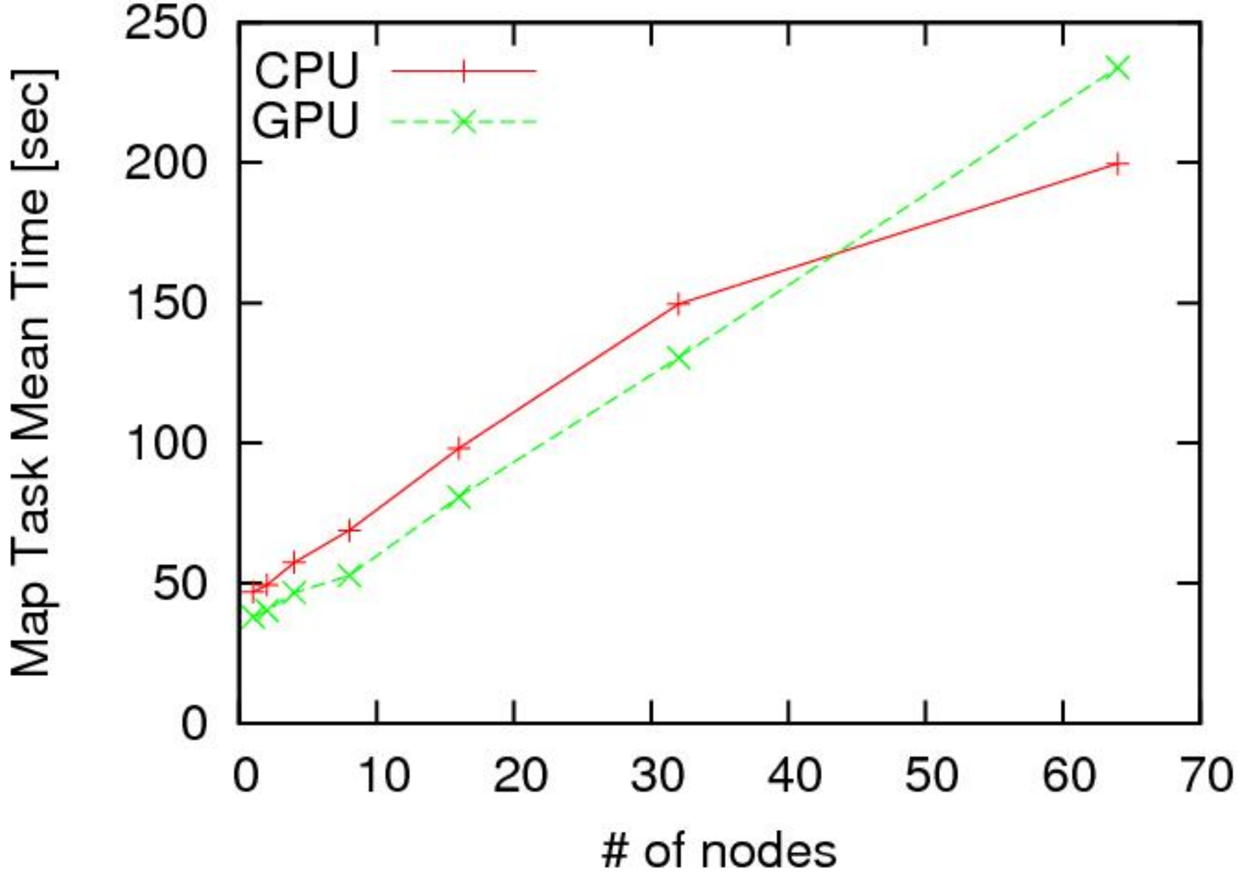
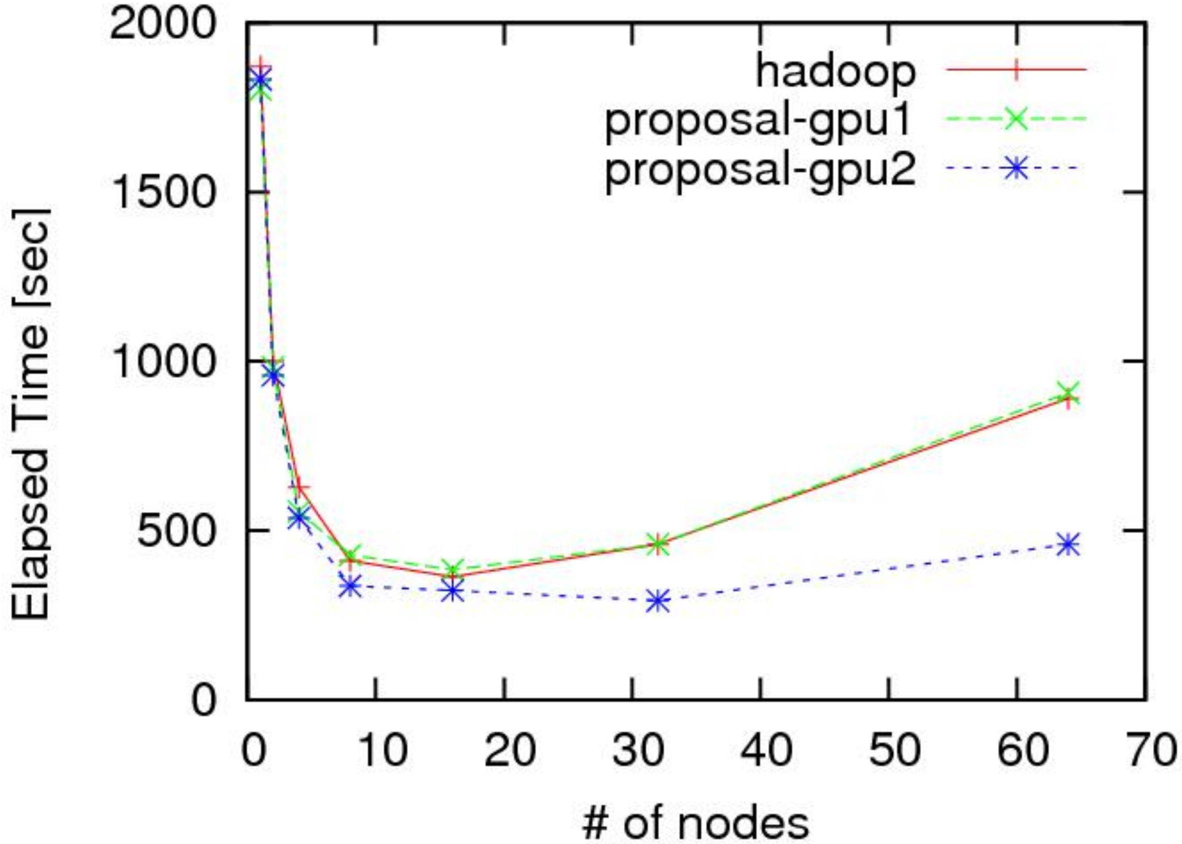
Increase of Map task runtime

- Map task runtime increases in proportion to # of nodes
  - Degradation of I/O performance
  - Since Lustre is configured with separated compute and storage node connected with shared networks



Comparison of job execution time 1 GPU / node with 2 GPUs / node



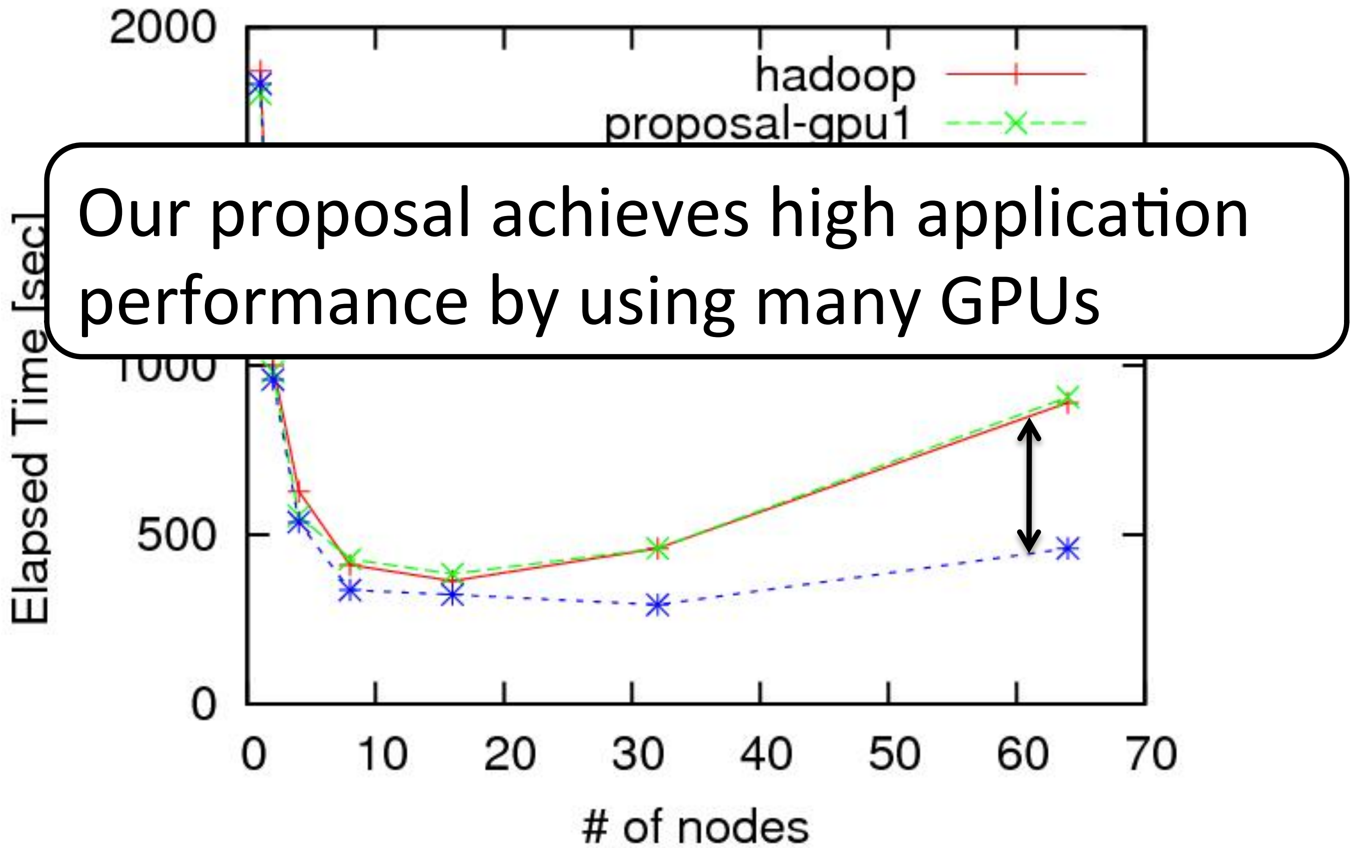
Total MapReduce job execution time

-hadoop: Hadoop original scheduling

-proposal-gpu1: Proposed scheduling with 1 GPU device / node

-proposal-gpu2: Proposed scheduling with 2 GPU devices /node

Comparison of job execution time 1 GPU / node with 2 GPUs / node



Total MapReduce job execution time

-hadoop: Hadoop original scheduling

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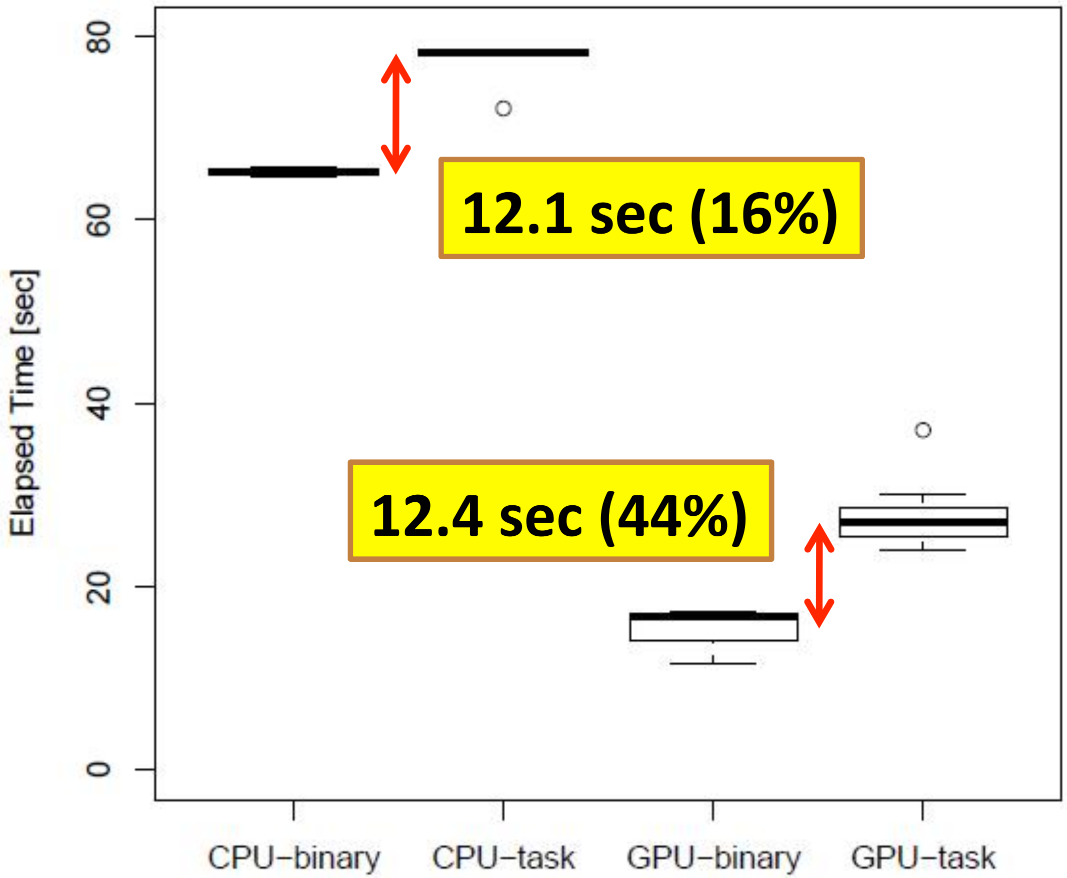
-proposal-gpu2: Proposed scheduling with 2 GPU devices /node

Overhead of process launching
Experiment with 1 node

- Compare Map task binary runtime and Map task (total) runtime
  - Binary time: C++ or CUDA Map function execution time
  - Map task runtime: from Map task allocation to finish of the task



→ Significant overheads dependent on original Hadoop implementation

CPU-binary, GPU-binary : binary execution time

CPU-task, GPU-task : Map task runtime

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Related work

- Several studies related to task scheduling or hybrid execution
  for heterogeneous environment
  - CPU/GPU task scheduling by learning mechanism [Chi-Keung Lu et al. `09]
  - Accelerate reduction computation with CPU/GPU hybrid execution by changing chunk size [T. Ravi Vifnesh et al. `10]
  - MapReduce task scheduling in heterogeneous environment [Zaharia et al. `08]

→ Massive data processing by CPU/GPU hybrid execution according to computing resource/ application

- Consider resource contention (e.g. memory, storage)
- Auto-scheduling during execution

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Conclusion and Future work

- Conclusion
  - Invocation of Map task on GPU from Hadoop
  - Task scheduling technique for GPU-based heterogeneous environment
  - Experiment by K-means application
    - 1.02-1.93 times faster by 2GPUs / node and proposed technique
    - Significant overhead dependent on Hadoop implementation
- Future work
  - Bottleneck analyses
    - TSUBAME 2.0, a new supercomputer in Tokyo Tech.
    - Comparison of Lustre and HDFS
  - Improvement of scheduling model
    - Resource contention issue including memory/disk access
    - I/O performance to storage system