Job Allocation Scheduler with locality for Efficient Deployment of MapReduce Applications in Heterogeneous Computing Environments

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1. ABSTRACT

Cloud computing has become increasingly popular model for delivering applications hosted in large data centers as subscription oriented services. Hadoop is a popular system supporting the MapReduce function, which plays a crucial role in cloud computing. The resources required for executing jobs in a large data center vary according to the job type. In Hadoop, jobs are scheduled by default on a first-come-first-served basis, which may unbalance resource utilization. This paper proposes a job scheduler called the *job allocation scheduler* (JAS), designed to balance resource utilization. For various job workloads, the JAS categorizes jobs and then assigns tasks to a *CPU-bound queue* or an *I/O-bound queue*. However, the JAS exhibited a locality problem, which was addressed by developing a modified JAS called the *job allocation scheduler with locality* (JASL). The JASL improved the use of nodes and the performance of hadoop in heterogeneous computing environments. Finally, two parameters were added to the JASL to detect inaccurate slot settings and create a dynamic job allocation scheduler with locality (DJASL). The DJASL exhibited superior performance than did the JAS, and data locality similar to that of the JASL.
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Keywords: Hadoop, heterogeneous environments, heterogeneous workloads, MapReduce, scheduling

2. INTRODUCTION

BIG DATA

"Big data" is a term used to describe a collection of data sets with the following three characteristics:

i. Volume- Large amounts of data generated.
ii. Velocity-Frequency and speed of which data are generated, captured and shared
iii. Variety-Diversity of data types and formats from various sources.

The size and complexity of big data makes it difficult to use traditional database management and data processing tools. Data is being created in much shorter cycles from hours to milliseconds. There is also a trend underway to create larger databases by combining smaller data sets so that data correlations can be discovered.

Big data has become the new frontier of information management given the amount of data today's systems are generating and consuming. It has driven the need for technological infrastructure and tools that can capture, store, analyse and visualize vast amounts of disparate structured and unstructured data. These data are being generated at increasing volumes from data intensive technologies including, but not limited to, the use of the Internet for activities such as accesses to information, social networking, mobile computing and commerce. Corporations and governments have begun to recognize that there are unexploited opportunities to improve their enterprises that can be discovered from these data.

3. Proposed work

An approach for balancing resource utilization in Hadoop systems in heterogeneous computing environments such as clouds.

To overcome the limitations of current mapreduce application platforms, we first proposes a job scheduler called job allocation scheduler (JAS) for balancing resource utilization in heterogeneous computing environments. The JAS divides jobs into two classes (CPU and I/O bound) to test the capability of each TaskTracker According to the capacity ratio for job types to maximize resource utilization.
The proposes a modified JAS, called job allocation with locality(JASL).The JASL can record each node's execution time, and then compare the execution times of the local and non-local nodes too determine whether the task can be executed on non-local node.in addition , an enhased JASL , called dynamic job allocation scheduler with locality(DJASL), was developed by adding a dynamic function to the JASL.

4. System architecture

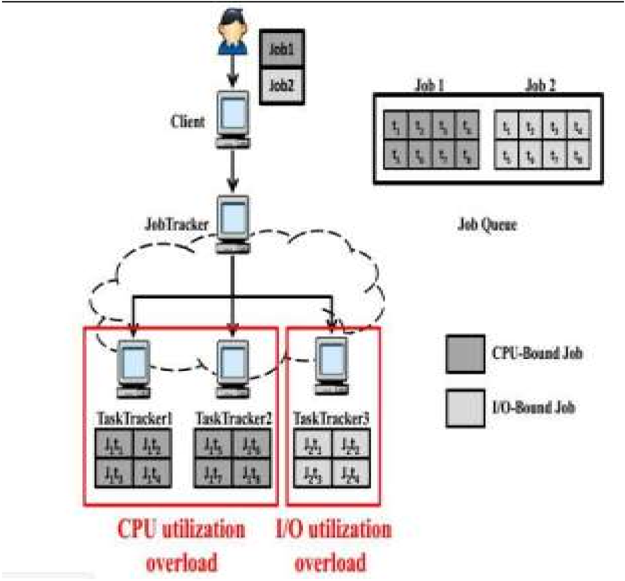
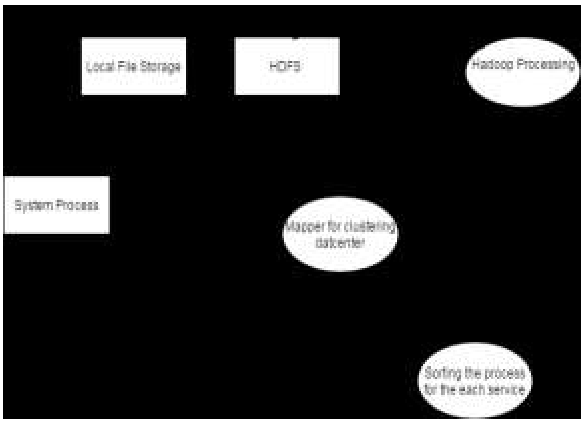


Fig: System Architecture

DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.


Local File Storage
HDFS
Hadoop Processing
System Process
Mapper for clustering datcenter
Sorting the process for the each service

.

5. Algorithm

Job queue (set CPU-slot)

```
for Job in Job Queue do
    if Job has been completed and Job is CPU-bound then
        obtain the task information from TaskTrucker;
        compute the TaskTrucker capability according to TaskTruckerCPUCapability;
        $c_y := \frac{|M_y|}{e_y}$;
        for each TaskTrucker do
            $k_y :=$ (the number of CPU slots) $* \frac{c_y}{\sum_{j=1}^{m} c_j}$;
            record $k_y$ on TaskTruckerCPUTable;
            SetTaskTruckerCPUTable := 1;
        return TaskTruckerCPUslot according to TaskTruckerCPUTable;
        break;
```

It reads the execution of job time

Job queue(set I/O_slot)

```
for Job in Job Queue do
    if Job has been finished and Job is I/O-bound then
        obtain the task information from TaskTracker;
        compute the TaskTracker capability according to TaskTrackerIOCapability;
        $d_y := \frac{n_y}{f_y}$;
        for each TaskTracker do
            $i_y :=$ (the number of I/O slots) $* \frac{d_y}{\sum_{j=1}^{m} d_j}$;
            record $i_y$ onTaskTrackerIOTable;
            SetTaskTrackerIOTable := 1;
        return TaskTrackerIOslot according to TaskTrackerIOTable;
        break.
```

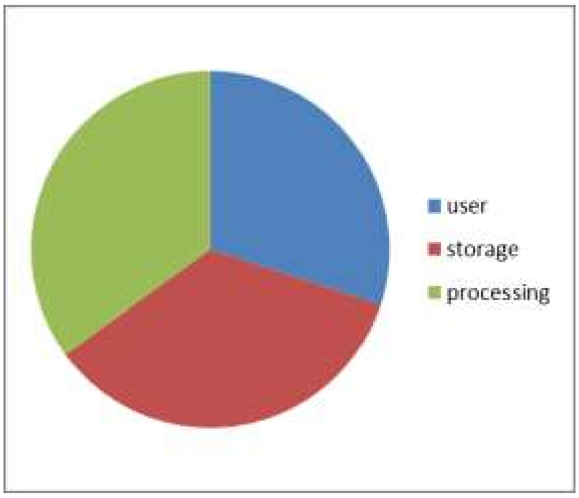
In this algorithm the input data's slots are given time for every task.

DJASL

```
When a batch of jobs are submitted into JobTracker:
add jobs into Job Queue;
Initialize SetTaskTrackerCPUTable := 0;
Initialize SetTaskTrackerIOTable := 0;
Initialize CPUcount := 0;
Initialize IOcount := 0;
Initialize LocalityBenifitTable := 0;
while receive Heartbeat by TaskTracker do
    TaskTrackerCPUslot := 0;
    TaskTrackerIOslot := 0;
    obtain TaskTrackerRunningCPUtask from Heartbeat information;
    obtain TaskTrackerRunningIOtask from Heartbeat information;
    AvailableCPUSlots := 0;
    AvailableIOSlots := 0;
    JOB_CLASSIFICATION_L(Heartbeat);
    if SetTaskTrackerCPUTable == 1 then
        obtain TaskTrackerCPUslot according to TaskTrackerCPUTable;
    else
        TaskTrackerCPUslot :=SET_CPU_SLOT(Job Queue);
    if SetTaskTrackerIOTable == 1 then
        obtain TaskTrackerIOslot according to TaskTrackerIOTable;
    else
        TaskTrackerIOslot :=SET_IO_SLOT(Job Queue);
    if TaskTrackerCPUslot == 0 then
        TaskTrackerCPUslot := default CPU slot;
    if TaskTrackerIOslot == 0 then
        TaskTrackerIOslot := default I/O slot;
    if TaskTracker.CPUusage > 90% of CPU usage then
        CPUcount += 1;
    if TaskTracker.IOusage > 35MB then
        IOcount += 1;
    if CPUcount >= 100 then
        reset CPU_slot;
    if IOcount >= 100 then
        reset I/O_slot;
    AvailableCPUSlots := TaskTrackerCPUslot − TaskTrackerRunningCPUtask;
    AvailableIOSlots := TaskTrackerIOslot − TaskTrackerRunningIOtask;
    CPU_TASK_ASSIGN_L(AvailableCPUSlot);
    IO_TASK_ASSIGN_L(AvailableIOSlot).
```

When the frequency is overload it can maintain the tasktracker.

6. Result analysis



7.Conclusion

The JAS provide highly efficient job scheduler for hadoop system .according to the job tracker first computes the capability of each task tracker and then sets the no.of CPU and I/Pslots accordingly

The DJASL also improved the data locality of the JAS by approximately 27% this scheduling alg is not only useful for hadoop system but also applicable to other cloud software systems as YARN and Aneka

8. Future Enhancement

In the future the characterization and performance comparisons of CPU and I/O-bound jobs will be provided.

CPU and I/O-bounds can be parallelized to balance resource utilization.

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