Research on Hadoop Job Scheduling Based on an Improved Genetic Algorithm

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Abstract

Hadoop job scheduling is an important influence factor in the performance of the Hadoop platform. Due to its characteristics, genetic algorithm (GA) has natural parallel advantages in job scheduling. But the scheduling based on the traditional simple genetic algorithm (SGA), in the aspect of the average execution time of job, the convergence speed and the selection of the optimal solution, is lack of consideration, which cannot make full expression of its advantages. We propose an improved genetic algorithm, which adopts the reserved strategy of optimal solution to speed up the convergence speed. The experimental results indicate that the proposed algorithm has a certain improvement on the scheduling efficiency and the performance of platform.

Keywords: Hadoop, Genetic Algorithm, CHC, The optimal solution

1. Introduction

Apache Hadoop [1] is an open source distributed platform, mainly composed of two core projects, namely distributed computing framework Map/Reduce [2] and distributed file storage system HDFS [3]. With the rise of big data [4], Hadoop, with the advantages of its own, has attracted a lot of IT companies. After years of research and development, Hadoop has been large-scale used in the field of data processing, but also get the wide attention of the academia.

In the study of Hadoop, job scheduling is always the key point of the research, because it is an important link of impacting the performance of the platform. Hadoop platform itself has three kinds of scheduling methods: Job Queue TaskScheduler based on FIFO mechanism, Fair Scheduler and Capacity Scheduler. In addition, there are many scheduling policies for different environment and different job, such as dynamic scheduling based on heterogeneous load, real-time scheduling, etc. Processing mode of job in Hadoop is to split a big job in small tasks, then different tasks are assigned to each task engine to execute. This is a kind of distributed programming ideas from Google, and Map/Reduce programming model in Hadoop is an open source implementation of the idea. It is very suitable for processing large data set. Its data processing consists of five stages, InputFormat, Map, Partition, Reduce, and OutputFormat. And reduce stage is depending on Map stage. The data processing of Map/Reduce is as follows.

![Figure 1. The Data Processing of Map/Reduce](image-url)
The purpose of job scheduling is how to allocate different tasks to suitable task machine, to make job completion time shorter, and at the same time make utilization of task machine higher. In the process of task allocation, many constraints need to be comprehensively considered, including the network bandwidth, load of each node, failure, performance, data locality, etc. So, this is a kind of combinatorial optimization problem, also a kind of NP problem. Genetic algorithm has intelligent features of self-organizing, self-learning and self-adaption, and parallelism of itself. It is a powerful tool in solving the problems of combinatorial optimization, the job scheduling, etc. Therefore, the combination of genetic algorithm and job scheduling can cope with such difficulties and seek a satisfactory solution. In this article, based on an improved genetic algorithm, which is an improvement of the traditional simple genetic algorithm, we comprehensively consider the optimal solution retention strategy and the constraint conditions that mentioned above, simulating and obtaining approximate optimal solution as soon as possible. In genetic algorithm, this Map/Reduce process will be considered in the form of an overall. So it can make scheduling approach more concise, without too much focusing on the processing of task.

2. Related Work

The process of Hadoop job scheduling is shown in Figure 2. The Client submits a job to the JobTracker and notifies the task scheduler. When TaskTracker asks for new task to the JobTracker, TaskScheduler, with the task request information from JobTracker, return the task list. Finally TaskTracker launches assigned task.

![Figure 2. The Process of Hadoop Job Scheduling](image)

The function of job scheduling is to assign computing resources of different TaskTracker nodes to the tasks in cluster by certain strategies. In the Hadoop job scheduling, itself contains three kinds of schedulers, but it is difficult to meet user’s quickly changing needs. In Hadoop, task scheduler is designed to be a pluggable module, and it can be flexible to cope with different applications. So it has appeared many new scheduling algorithms and the improved scheduling algorithms. In general, they can be divided into two classes: the non-intelligent algorithm and intelligent algorithm.

Non-intelligent algorithm is mostly aimed at the bottleneck factors for innovation and improvement in the process of scheduling. The algorithm is simple, and has more research results, but the configuration is complex. Intelligent algorithm is simulation and application of biological activity or neural behavior. So, the algorithm is long process, high complexity and less research results, but the configuration cuts, and it is more efficient than the non-intelligent algorithm in the huge amounts of data.
In the non-intelligent algorithms, LATE scheduling algorithm [5], [6] is based on task speculation mechanism. It is more likely to find "dragger" task, launches the backup task ahead of time, and effectively shortens the execution time in a heterogeneous cluster environment. SAMR algorithm [7] is based on the LATE algorithm, using dynamic way to compute task progress, and it improves the accuracy of scheduling information. Delay scheduling algorithm [8] is a scheduling method that it ignores fairness in order to improve the data locality of task. Dynamic priority scheduling algorithm [9] allows the user to dynamically adjust priority of job and allocates task proportionally.


In Hadoop, job scheduling belongs to the category of the combinatorial optimization, and is a multi-objective problem, also a typical NP problem. Intelligent algorithm usually has a good performance on the NP problems. Genetic algorithm is a kind of excellent intelligent algorithm, and meets the optimality principle. Its solving way is simulating population evolution mechanism, generational circulation, finally retaining the optimal solution of set. This is the basic theory of a Hadoop job scheduling using genetic algorithm. According to this, in this paper we propose a Hadoop job scheduling algorithm based on CHC genetic algorithm.

3. The Problem of Job Scheduling Based on Traditional Genetic Algorithm

The process of Simple Genetic Algorithm(SGA) is as follows.

<table>
<thead>
<tr>
<th>Algorithm1: Simple Genetic Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>define global variable;</td>
</tr>
<tr>
<td>void initPopulation();</td>
</tr>
<tr>
<td>void calInitFit();</td>
</tr>
<tr>
<td>void calFit();</td>
</tr>
<tr>
<td>void generation(){</td>
</tr>
<tr>
<td>int select();</td>
</tr>
<tr>
<td>int crossover();</td>
</tr>
<tr>
<td>void mutation();</td>
</tr>
<tr>
<td>}</td>
</tr>
<tr>
<td>main()</td>
</tr>
</tbody>
</table>

The SGA algorithm is making simply parallel processing for task, screening the optimal solution only by the genetic operations. So there are the following questions, 1) The evolutionary generations is long, and convergence speed is slow. 2) For the optimal solution is not to do special processing, it may be lost in the process of evolution. 3) The SGA algorithm is only considering the total completion time of job, ignoring the differences between big jobs and small jobs, lack of consideration for average completion time of job.

In view of the above three drawbacks, in this paper we propose a job scheduling method based on improved genetic algorithm. The algorithm sacrifices simplicity of SGA algorithm in exchange for a better parallelism genetic effect [13], at the same time emphasizing the optimal solution retention strategy and accelerating the convergence speed.
4. Job Scheduling Based on Improved Genetic Algorithm

4.1. Related Definition

The goal of improved genetic algorithm proposed in this paper is that the total completion time is shortened and the average completion time is short as far as possible. At the same time, giving consideration to the optimal solution, and achieving rapid convergence.

Before job is scheduled, *JobTracker* node calculates the average task completion time by the table 1 and table 2. Suppose there are m Jobs and n *TaskTracker* nodes. In which $l_i$ represents the splitting number of each job, $b_i$ represents the maximum number of *TaskTracker* that is available for each job. By default every $b_i$ value is equal. When the failed node arising or dynamically adding or removing nodes in the cluster, it will change, $1 \leq i \leq m$. $S_i$ represents the number of parallel slots in *TaskTracker* node. It can be dynamically read from the configuration file and dynamically changes as the stage of task, which is Map process or Reduce process, $1 \leq i \leq n$.

<table>
<thead>
<tr>
<th>Job</th>
<th>Splitting number</th>
<th>Maximum number of TaskTracker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job1</td>
<td>$l_1$</td>
<td>$b_1$</td>
</tr>
<tr>
<td>Job2</td>
<td>$l_2$</td>
<td>$b_2$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Jobm</td>
<td>$l_m$</td>
<td>$b_m$</td>
</tr>
</tbody>
</table>

Table 2. The Configuration of Tasktracker

<table>
<thead>
<tr>
<th>TaskTracker</th>
<th>Number of parallel slots</th>
</tr>
</thead>
<tbody>
<tr>
<td>TaskTracker1</td>
<td>$S1$</td>
</tr>
<tr>
<td>TaskTracker2</td>
<td>$S2$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>TaskTrackern</td>
<td>$S_n$</td>
</tr>
</tbody>
</table>

*JobTracker* calculates the data of table 1 and table 2, and obtains the average execution time $TT$ of $Job_m$ on *TaskTracker*$_n$.

<table>
<thead>
<tr>
<th>Job</th>
<th>$TT_1$</th>
<th>$TT_2$</th>
<th>...</th>
<th>$TT_n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job1</td>
<td>$\bar{t}_{11}$</td>
<td>$\bar{t}_{12}$</td>
<td>...</td>
<td>$\bar{t}_{1n}$</td>
</tr>
<tr>
<td>Job2</td>
<td>$\bar{t}_{21}$</td>
<td>$\bar{t}_{22}$</td>
<td>...</td>
<td>$\bar{t}_{2n}$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Jobm</td>
<td>$\bar{t}_{m1}$</td>
<td>$\bar{t}_{m2}$</td>
<td>...</td>
<td>$\bar{t}_{mn}$</td>
</tr>
</tbody>
</table>

Among them, the scheduling order of different jobs on each task machine is allocated in the following way. Assume that there are three jobs, the allocation of subtask on *TaskTracker*$_1$ is as the following,
Considering the differences between different jobs and the fairness of scheduling, TaskTracker complies with the order \{t_{11}, t_{21}, t_{31}, t_{12}, t_{22}, t_{32}, t_{13}, t_{33}, t_{14}\} to schedule jobs. So that we can ensure a timely response of small job and execution time of big job [14].

Because the processing speed of the machines is different, the type of tasks is different, and the tasks group by parallel slots, so the sequence of completion of task is uncertain. It is more accurate to solve completion time of task with waiting time adding execution time, but the uncertainty of the sequence of completion can also led to the uncertainty of solution. So choosing the average execution time is an effective method. In the process of scheduling, to get the average task execution time by the final completion moment of each job minus the starting time, divided by the norm of the task.

\[
\overline{t_{\text{mn}}} = \frac{t'_{\text{mn}} - t_0}{\|T'_{\text{mn}}\|}
\]

Among them, \(\|T_{\text{mn}}\|\) represents the norm of the subtask set Job\(_m\) of TaskTracker\(_n\). \(t'_{\text{mn}}\) represents completion time of final task in subtask set Job\(_m\) of TaskTracker\(_n\). \(t_0\) represents the beginning execution time of the first task in TaskTracker\(_n\). By the above definition, we can get objective function and the corresponding constraints according to the scheduling goal.

4.2. The Mathematical Model of Improved Genetic Algorithm

4.2.1. Objective Function

The proposed algorithm is based on the total completion time and the average completion time, the mathematical equation as below.

\[
\begin{align*}
    f(i, j) &= \min \left[ v \max_{j=1}^{u} T_{ij} + u \sum_{i=1}^{v} T_{ij} \right] \\
    f(i) &= \min_{i=1}^{u} \left[ v \max_{j=1}^{u} T_{ij} \right]
\end{align*}
\]

Where \(T_{ij}\) represents execution time of subtask set of job \(u\) on TaskTracker\(_n\).

4.2.2. Constraint Condition

1. The total tasks of Job, assigned to all TaskTracker nodes cannot exceed the number of splitting \(l\).

\[
\sum_{j=1}^{u} \|\text{Job}_j\| \leq l
\]
The concurrent tasks of each TaskTracker cannot exceed setting value, at the same time, the total number of concurrent cannot exceed 90% of the total slots in cluster. A part of resources are set aside, in the node failure or other unexpected circumstances supplied for TaskTracker.

\[
\begin{align*}
\|TaskTrac\|_j \leq s_j \\
\sum_{j=1}^{n} \|TaskTrac\|_j \leq 0.9 \sum_{j=1}^{n} s_j
\end{align*}
\]

(4)

### 4.3. Improved Genetic Algorithm

#### 4.3.1. Encoding and Decoding

In this paper, we adopt a direct encoding way that it is distributed between Job-TaskTracker according to the task set of job. A chromosome is expressed in the form of matrix, \( Y = [T_{ij}]_{i=1,\ldots,m, j=1,\ldots,n} \), which \( i \) represents the number of job involved in the scheduling, \( j \) represents the number of TaskTracker node in cluster. \( T_{ij} \) is a subtask set, represents allocated subtask set of job \( i \) on node \( j \).

<table>
<thead>
<tr>
<th>Table 4. Coding and Decoding Table</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>Job(_1)</td>
</tr>
<tr>
<td>Job(_2)</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>Job(_u)</td>
</tr>
</tbody>
</table>

Which \( T_{uv} \) is subset of taskset \( \{t_{u1}, t_{u2}, \ldots, t_{um}\} \) of job Job\(_u\) [15]. There are constraints on the job as shown in equation 5.

\[
\begin{align*}
\bigcup_{r=1}^{n} T_{uv} &= Job_u \\
\bigcap_{r=1}^{n} T_{uv} &= \emptyset
\end{align*}
\]

(5)

#### 4.3.2. The Generation of Initial Population

As there is no any prior conditions about the allocation of the job, so we adopt the randomly generated method, and to satisfy the constraint conditions. Here, the population size is 100.

The generation step of initial population is as follows.

**Step1:** Make all elements in the matrix \( Y \) empty, namely \( T_{ij} = \emptyset \).

**Step 2:** In order to keep the balance of assigned tasks, each TaskTracker divides task according to its own parallel number of slots in the proportion of total number of slots. Firstly to determine the size of the set of tasks, and then randomly assign task according to the size.

**Step 3:** Checking Job and TaskTracker whether meet the constraint (3) (4) (5).

**Step 4:** Looping execute the first two steps until the population size.
4.3.3. Fitness Function

Fitness function decides the merits of the individual, so that more superior individual is selected in the next round of evolution.

Therefore it is critical to select fitness function. And it is closely related with the convergence speed, if you can find out the optimal solution. Here directly to the objective function as the fitness function, namely, \( F(x) = f(x) \).

4.3.4. Genetic Operation

(1) Individual selection

Firstly, individual selection is based on the optimum solution, namely the locality of task. In the algorithm it is as the first factor to consider. Here individual selection is based on sorting method. Firstly for each round scheduling of individual, to calculate the objective function value. Then ascending sort according to the scheduling result, the corresponding individual of the larger objective function value is eliminated (elimination rate 10%). So that we can eliminate bad genes, as soon as possible to ensure the rapid concentration of good genes, to speed up the convergence. Figure 4 and Figure 5 is a scheduling of two parent individuals.

![Figure 4. Parent1](image-url)
(2) Crossover operation

Due to the crossover operation has constraint conditions on Job rows and TaskTracker columns, and to ensure retention strategy of the optimal solution. Therefore, we use a method of multipoint crossover. Crossover columns are randomly selected (see Figure 4, Figure 5 mark 1, 2, 3 column), and these columns meet the following conditions: The column including locality task does not participate in cross; The column removing locality node, participate in cross columns contain equal tasks, to calculate by row; If there is no such column, skip this round of crossover; At the same time, the order of the job in a row is strictly determined, remaining the same in the process of crossover.

(3) Mutation operation

Individual matrix is used for mutation operation, randomly selecting two column to exchange (see Figure 6), which the column of data locality will not be involved.

So that the optimal solution is retained for each generation, and obtains a quick convergence.

![Figure 5. Parent2](image)

![Figure 6. The Process of Mutation Operation](image)
4.3.5. The Determination of The Optimal Solution

After the genetic operation is completed, all individual of father and son will be a new species. Back to the stage of fitness testing and sorting for the operation of the population, if the evolution of the population does not reach the generations, the algorithm continue the genetic operation. Otherwise, the algorithm selects first element in the scheduling queue into the decoding stage, namely the $T_g$ set is one-time assigned to the corresponding TaskTracker node.

4.4. The Overall Process of Job Scheduling by Improved Genetic Algorithm

The process of the improved genetic algorithm are almost consistent with the SGA algorithm. The main difference lies in the selection and retention strategy of the optimal solution in every step of evolutionary process. The overall process of job scheduling by improved genetic algorithm is as follows.

5. Experiment

There are four different configurations in cluster with a gigabit switch connected, as shown in table 5, and this ensures the heterogeneity of the cluster [16],[17], simulating the evolution of the individual and the actual cluster environment. The whole cluster consists of a JobTracker node and 13 TaskTracker nodes. The configuration of each node are shown in table 5. The software version are Ubuntu 12.04 operating system and Hadoop 1.0.4. Choosing RandomWriter to randomly generate test data, and benchmark test program of using TeraSort to sort.
<table>
<thead>
<tr>
<th>Cluster</th>
<th>Configuration</th>
<th>Number</th>
<th>Role</th>
</tr>
</thead>
<tbody>
<tr>
<td>VM₁</td>
<td>MM: 4 GB</td>
<td>1</td>
<td>JobTracker</td>
</tr>
<tr>
<td></td>
<td>CPU: 2.00 GHz×4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VM₁</td>
<td>MM: 2 GB</td>
<td>4</td>
<td>TaskTracker</td>
</tr>
<tr>
<td></td>
<td>CPU: 2.00 GHz×2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VM₁</td>
<td>MM: 2 GB</td>
<td>5</td>
<td>TaskTracker</td>
</tr>
<tr>
<td></td>
<td>CPU: 2.68 GHz×2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Desktop</td>
<td>MM: 2 GB</td>
<td>3</td>
<td>TaskTracker</td>
</tr>
<tr>
<td></td>
<td>CPU: 3.00 GHz×2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laptop</td>
<td>MM: 2 GB</td>
<td>1</td>
<td>TaskTracker</td>
</tr>
<tr>
<td></td>
<td>MM: 4 GB</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This experiment mainly tests the performance of algorithm from two aspects, total completion time and the average completion time of job. The test results are shown in Figure 8 and Figure 9. From Figure 8, we can see completion time of the job falling faster in the beginning. This is due to the bad gene is knocked out, good genes quickly gathered process. With the increase of evolution generations, the pace of decline is in gradually reducing. This is due to the accumulation of the good genes, and algorithm increase rate will slow down gradually. Finally at about the 40th generation basically achieve stability. This is due to the reservation of optimal solution, to speed up the accumulation of good genes. To greatly reduce evolution generations of reaching the optimal solution.

Figure 8. The Total Completion Time of Job

From Figure 9, we can see that the decreasing trend of the average completion time is basically as well as the total completion time. Evolved to around 20 generations it has a small recovery. It is because of the effect of many factors, such as the uncontrollable variation, the performance of the machine, the network situation, and many other conditions. But this is only a small probability event. The final trend is still down and stable.
6. Conclusion

In this paper, on the basis of simple genetic algorithm, we propose a Hadoop job scheduling algorithm based on improved genetic algorithm. With reserved strategy of the optimal solution, setting different constraint detection, speeding up the convergence speed of the algorithm, and the job in the two aspects of total completion time and the average completion time has certain promotion. At the same time, the resource utilization of TaskTracker node is also improved. But the weight coefficient in the constraint condition is set by the experience value, not necessarily applying to the heterogeneous cluster. Therefore, in the next step we will research the problem of the dynamic allocation of weight coefficient.

References


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