

OpenCL and CUDA Comparison of MapReduce Performance on Distributed Heterogeneous Platform through Integration with Hadoop Cluster

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Abstract

An effective processing of Big Data in various application areas is an important task today. Modern development of information technology provides the ability to calculate a large number of different tasks using a certain number of computers in distributed mode. MapReduce technology allows to perform distributed calculations on a huge amount of data by dividing them into parts, performing parallel calculations of each of them and combining the results. In this paper, experimental studies were performed to compare CUDA and OpenGL frameworks performance measurements for MapReduce operations on heterogeneous cluster. It has been found that CUDA is a more suitable framework that provide a significant advantage in this regard. It is determined that the greater the amount of processing data, the greater the delay caused by OpenCL. Further research will be conducted to determine the energy consumption of both technologies.

Keywords 1

OpenCL, CUDA, performance evaluation, Hadoop cluster

1. Introduction

Dramatic demand for usage of big data processing technologies has been observed during last few years. Simultaneously, general-purpose GPU accelerated computation frameworks develops. Both techniques are being used in similar fields eg. data science [1], data processing [2], data mining [3], machine learning [4], [5], solving various biological [6], [7], medical [8], [9], physical [10] and geographical [11] problems. Consequently, many research studies have been made to compose scalability of big data processing systems with maximization of resources usage and performance of GPU powered computations. Those attempts aim improving performance [12], power-usage [13], deal with low capacity of GPU memory [14] and improve programmability [2] of this approach

Computation using graphic processors can speed up any type of calculations. The technique is called GPGPU – general-purpose GPU [15]. It is possible to implement MapReduce's reduce operation using previously mentioned GPU computing frameworks in order to speed-up whole algorithm. GPGPU enables to run a code on way more cores than standard CPU. Although GPU is not designed for general usage and has significantly less memory that CPU [16], well designed algorithm can speed up computations of many different kinds

The main goal of this paper is to compare performance of basic algorithm which aggregates results by sum. We test both CUDA and OpenCL™ implementations. CUDA and OpenCL are frameworks

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which enable using GPU for non-graphic related computing [17]. They provide GPU acceleration for mass parallel computation that can potentially speed-up MapReduce algorithms execution [14].

To achieve our goal we use Apache™ Hadoop® [18] powered heterogeneous cluster. Algorithms are implemented according to MapReduce paradigm in CUDA and OpenCL. Apache Hadoop is a software framework for distributed computing dedicated for big data processing. Its environment consists of connected workstations forming a cluster.

MapReduce is a paradigm for constructing algorithms dedicated to run on distributed environment [19]. It is supported by Apache Hadoop framework. It allows to spread process of computing among workstations connected into Hadoop cluster. It enables relatively fast processing of large amount of data by making the process parallel. Hadoop implements scheduling algorithm for optimal nodes resources usage and techniques for error recovery

We measure performance by measuring time taken to execute widely used MapReduce algorithms implemented with two leading GPU general purpose computation frameworks - CUDA and OpenGL. CUDA [17] is a framework dedicated for NVIDIA graphics cards while OpenCL [20] is multi-platform framework which computes using every found CPU and GPU resource available on a host machine. This means that what we measure is an overhead introduced by OpenCL in the specific environment of Hadoop based heterogeneous cluster.

Other approaches include using other distributed computation frameworks such as MPI. However, these are lesser fault-tolerant than Hadoop [1], [21]. On the other hand, consequence of using Hadoop and MapReduce paradigm forces redesigning data processing algorithm so as they fit into specific schema. Some techniques of visual programming may be applied to overcome this issue [2], but it does not ensure correctness of designed solution

There are many different systems that strive in the field of some kind of GPU powered MapReduce paradigm implementation. For example:

1. HAPI [22]

Hadoop combined with Aparapi – Java-to-OpenCL conversion tool developed and released by AMD. Proposes easy and ready to use API for designing and implementation of GPU MapReduce algorithms. By hiding complexity of GPU programming by system of annotations, allows programmers to focus on developing good algorithms.

2. HadoopCL [1]

Extension to Apache Hadoop, HadoopCL combines Hadoop and OpenCL by usage of Aparapi. Provides easy and flexible programming interface, guarantees reliability and low power consumption. States that it achieves nearly 3x overall speedup and 55x of computational sections of example MapReduce application algorithms.

3. GPMR [23]

GPMR is a stand-alone library for MapReduce that is supposed to use GPU clusters for large scale computing. By modifying MapReduce to combine large amounts of map and reduce items into chunks and partial reductions and accumulation, they better utilize power of GPU.

4. MITHRA [24]

An architecture that combines power of NVIDIA CUDA and Apache Hadoop to create scalable performance gains by utilizing MapReduce programming model. MITHRA was designed especially for executing computing tasks of massive and independent data.

5. MARS [25]

Mars is a MapReduce framework that is supposed to improve and ease programming complexity of GPU programming by a familiar MapReduce interface.

Authors of those systems compared their solutions with other works in terms of performance – however, reliable comparison of most popular GPGPU computation framework, that would be free of overhead ensuing from their framework usage, is still lacking

2. Proposed architecture

For the purpose of our research we have built a cluster containing 10 workstations, each of them hosting HortonWorks® Apache Hadoop framework implementation. Workstations use two different

physical configuration – differing with presence of GPU. Configuration consist of: Intel® Xeon® CPU E5-1630 v3 3.70 GHz, 16 GB RAM and optional NVIDIA Quadro K4200.

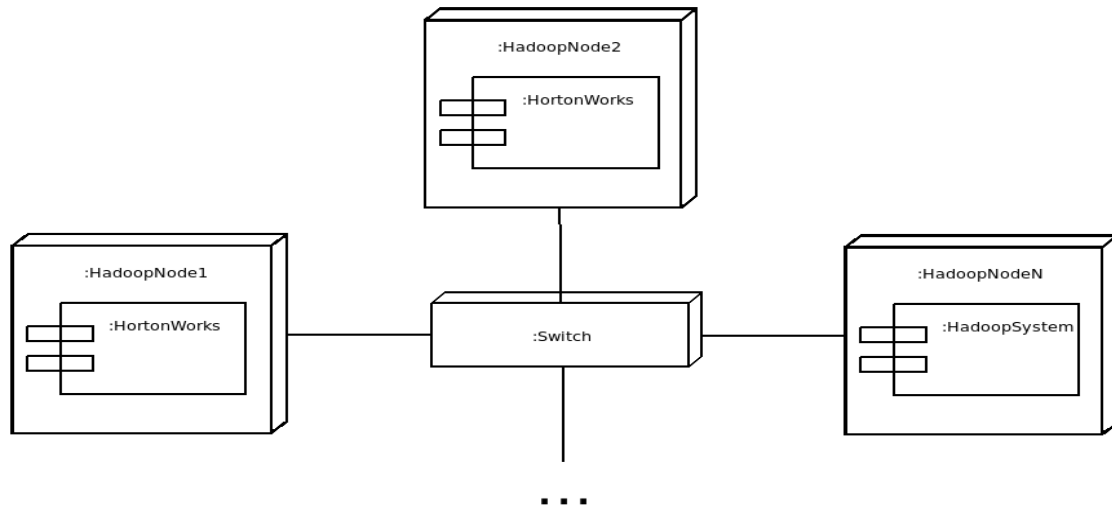


Figure 1: Architecture diagram. Own work

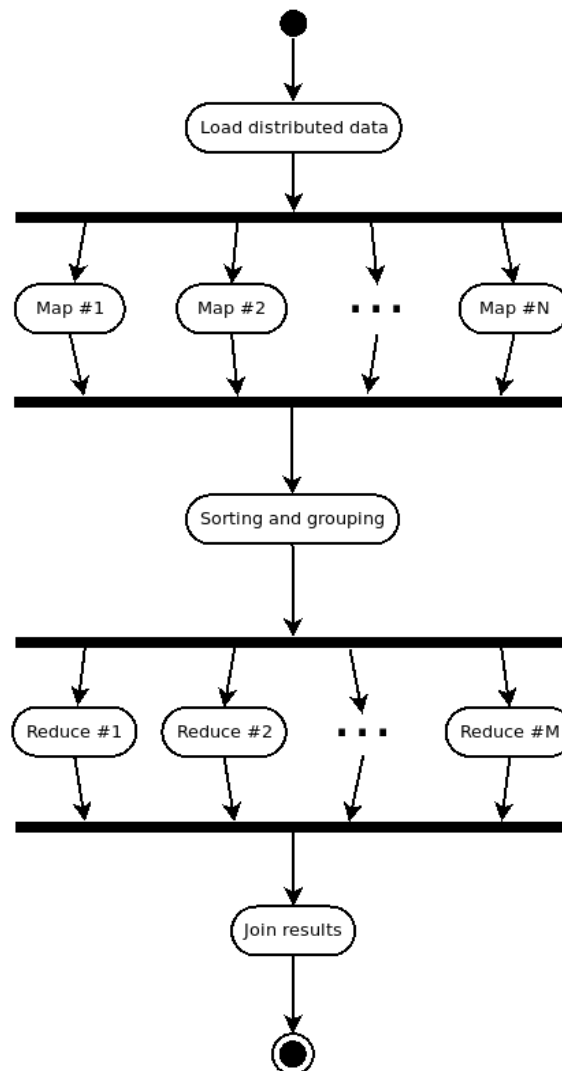


Figure 2: MapReduce data flow diagram. Own work.

Workstation are organized in star topology; they communicate with each other through a switch. Complete architecture can be found on Figure 1.

The area of work presented in this article are Apache Hadoop powered nodes. Hadoop schedules map and reduce tasks to be executed on a free node, preferably near to the place where input data are stored. In our approach this can lead to non-effective node usage because of a presence of GPU is irrelevant for scheduler when making a decision on which node certain task has to be executed. Some works have already been done in this field [26].

Our approach is to implement Reduce operation to move calculations and some algorithms from CPU to GPU.

3. Aggregation algorithm development

Basic idea behind our project is speeding up reduce operation (see Figure 2) using algorithms designed specifically for GPUs. As an example, we would use modified algorithm for calculation of exponent.

Exponent can be calculated using following formula [27]:

$$e^x = \sum_{n=0}^{\infty} \frac{x^n}{n!} \quad (1)$$

It is easy to notice that sum factors are independent, and as a result it is easy to calculate overall value by just summing up middle results (in any order).

When creating algorithm of fast sum calculation we inspired with NVIDIA publication [28] on parallel computation.

Basic idea behind it is following: having an array of numbers on length N, we can sum up pairs of elements, so complexity reduces from $O(N)$ to around $O(\log_2(n))$ (Figure 3).

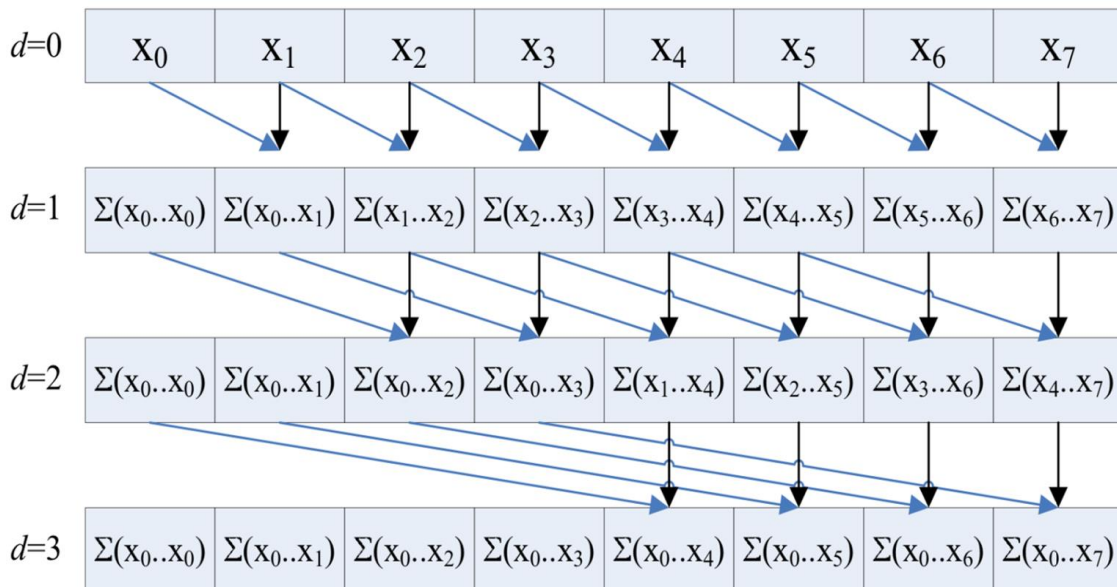


Figure 3: Illustration of naive summing algorithm. Source: [28]

As single operation is around simultaneous, speed-up is quite impressive. In order to achieve that with MapReduce in Hadoop we created modified implementations of map and reduce.

Map output was (key, value) pair where key was always 1, and value was n-th factor of the sum. As a result, after reduce operation we always got single key, and value which represents a result

4. Methodology

In this section, we describe methodology of our time performance analysis and comparison of MapReduce solution on both CUDA and OpenCL.

To measure a performance of the system we run several tests of exponent calculation, each of them differing number of jobs with and without GPU for both frameworks separately. The first test was run on only one GPU powered node. Then we have tested every number of nodes each kind starting from one to 10 total amount of nodes. All results were presented on charts below alongside with its discussion.

We measure performance, by measuring runtime of tests on all used nodes from sending data to each node, to receiving data from each node on master machine. Results often are shown as an improvement factor. This should be considered as execution time in certain case divided by execution time for non-GPU solution.

All the tests were run 5 times and presented results are average value. It was necessary due to the cache memory misses. Nevertheless, some small differences in similar measurements can be still observed.

5. Results

On the Figure 4 linear increase of computation time depending on the number of calculated elements can be observed. For our comparison the most significant information is difference between CUDA and OpenCL improvement. The results shows that usage of OpenCL generates latency in availability of computation results that linearly depends on the number of elements.

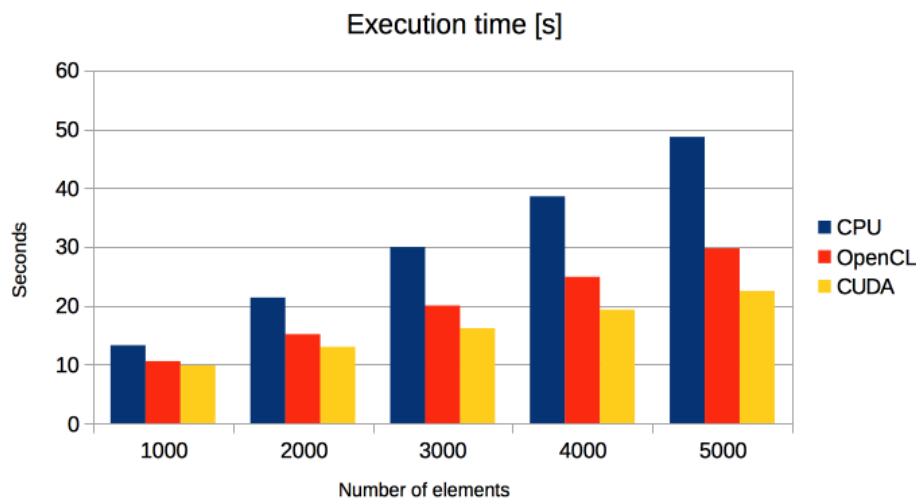


Figure 4: Execution time for various number of elements. Own work.

That means difference in improvement factor of execution time (Figure 5) between those two frameworks grows. These data were measured for very small – in terms of big data processing – number of elements. Big data algorithms usually work with millions of items. That implies that simple summation and memory move operations powered by OpenCL in big data analysis, when it comes to practical usage, can lead to significant superiority of CUDA over OpenCL.

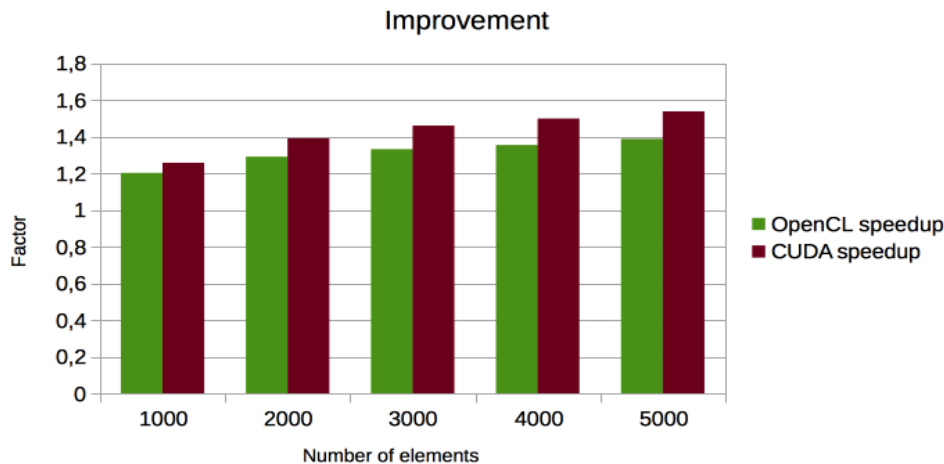


Figure 5: Improvement factor basing on execution time for each tested number of elements. Own work.

6. Conclusion

We have presented comparison of CUDA and OpenGL frameworks performance measurements for MapReduce operations on heterogeneous cluster. The results shows noticeable superiority of CUDA in this issue. Specifically, the biggest amount of is processed, the bigger OpenCL caused latency occurred to be. Nevertheless, it should be mentioned that CUDA is supported only by GPUs of the only one of two leading graphical cards manufacturers – namely NVIDIA. Therefore, this research does not solve the problem of the right framework choice for particular task on particular hardware resources available. Moreover, the comparison can be also done in the field of energy-saving [13].

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