

A Comparison of Parallel Graph Processing Platforms

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Abstract—In this paper we analyze the performance of four parallel graph processing systems to determine their performance and scalability using synthetic and real-world datasets. We perform analysis for three algorithms: breadth first search, single source shortest paths, and PageRank. This paper examines previously overlooked aspects of parallel programming performance such as file I/O in addition to a more detailed performance analysis.

I. INTRODUCTION

Our research is motivated by the current state of parallel graph processing. The most comprehensive survey, released in 2014, identified and taxonomized over 80 different parallel graph processing systems [4]. These systems operate with a wide range of parallelism paradigms and target architectures such as GPU [20], [12], shared memory [pretty much everything], a combination of CPU and GPU [6], distributed database querying, [17], distributed filesystem based approaches [19], distributed memory with MPI [10], domain-specific languages [9], as well as novel communication schemes [5].

Since 2014, the problem has compounded with the addition of even more proprietary and open source projects such as [3], [16] [name some more]. At the outset, this plethora of choices makes the question, “which system is the best for my problem?” daunting. There has even been a propagation of so-called “reference implementations” which implement the most common graph algorithms [cite GAP, GraphBIG, Galois]. Thus, even selecting a standard and a benchmark over which to compare various implementations is nontrivial. To quote Andrew Tanenbaum, “The nice thing about standards is that you have so many to choose from.”

Another issue among parallel graph processing systems is the lack of comprehensive comparisons. One possible reason for this is the considerable effort involved in getting each system to run: satisfying dependencies and ensuring correctly formatted data the data are nontrivial for most tasks. Beyond this, each system may have a different method of measuring performance. Thus, one of the contributions of this paper is to provide a “level playing field” for

each graph processing system. Graphalytics [2] attempts to remedy this but [state the limitations of graphalytics]

II. ALGORITHMS

The canonical performance leaderboard for parallel graph processing is the Graph500 [14]. The advantage of the Graph500 is it provides standardized measurement specifications and dataset generation. The primary drawback with the Graph500 is it measures a single algorithm: breadth first search (BFS).

This report attempts to add similar rigor to other graph algorithms. This is done by borrowing heavily from the Graph500 specification; we use a Kronecker graph [13] with initial parameters of $A = 0.57, B = 0.19, C = 0.19$, and $D = 1 - (A + B + C) = 0.05$. The Graph500 Benchmark 1 (“Search”) is concerned with two kernels: the creation of a graph data structure from an edge list stored in RAM and the BFS¹. Some clarifications are in order: for the first kernel, the time to read the graph from disk is not considered. Furthermore, these data structures need only be created once and BFS is performed on 64 roots. The second kernel creates a tree with distances from the root, but need only label the existing data structure (and not output the entire graph, for example).

One straightforward extension is computing the Single-Source Shortest Paths algorithm (SSSP). We use the same graph and the same source vertices as in BFS. We use SSSP and PageRank in this paper because of their simplicity and ubiquity.

III. THE EXISTING SYSTEMS

This report explores a small sample of the existing graph processing platforms with a focus on the so-called “reference implementations:” the Graph500², GAP [1], and GraphBIG [15]. GraphMat is also used because it has been cited as the most performant [cite]. Our target is shared memory CPU processing.

Other popular libraries such as the Parallel Boost Graph Library [8] are not considered here because they are a

¹For a complete specification, see <http://graph500.org/specifications>

²We used version 2.1.4 from <http://graph500.org/referencecode>.

PITA to get working and the authors never responded to my emails.

IV. MACHINE SPECIFICATIONS

Table I shows the specifications of the research computer (named Arya).

| | |
|--------------|------------------------------------|
| CPU Model | Intel Xeon(R) E5-2699 v3 @ 2.30GHz |
| CPU Sockets | 2 |
| CPU Cores | 72 |
| CPU Clock | 3600MHz |
| RAM Size | 256GB |
| RAM Freq | 1866MHz |
| Max RAM Freq | 2133MHz |
| GPU Model | GM204 [GeForce GTX 980] |

TABLE I

MACHINE SPECIFICATIONS. THE DISPARITY BETWEEN THE CPU'S ADVERTISED CLOCK SPEED AND THE "CPU CLOCK" ROW IS A RESULT OF THE TURBO BOOST TECHNOLOGY WHICH CAN INCREASE THE CLOCK SPEED TO A LIMIT. WE USE THE MANUFACTURER'S PUBLISHED MAXIMUM CLOCK SPEEDS WHICH CAN BE FOUND AT [HTTP://ARK.INTEL.COM](http://ark.intel.com).

V. PERFORMANCE

In Table II, BFS is breadth-first search, SSSP is single-source shortest paths, LCC is local clustering coefficient, PR is PageRank, CDLP is community detection using label propagation, and WCC is weakly connected components. For the algorithms used, see [11].

| | openg | powergraph |
|------|---------|------------|
| CDLP | 181.667 | 1226 |
| PR | 302.333 | 974 |
| LCC | 321.333 | 1036.67 |
| WCC | 87.6667 | 697.667 |
| SSSP | 4061.33 | 29022.3 |

TABLE II

PERFORMANCE RESULTS FOR THE DOTA-LEAGUE DATASET WITH 61,670 VERTICES AND 50,870,313 EDGES.

| System | Load Graph | Make Data Structure | Run BFS |
|----------|------------|---------------------|----------|
| Graph500 | 0.3474 | 0.3971 | 0.003380 |
| GraphBIG | 37.22 | N/A | 0.1528 |
| GraphMat | 0.1511 | 1.101 | 0.1031 |
| GAP | 2.351 | 0.1935 | 0.001393 |

TABLE III

TIMES ARE IN SECONDS. THE GRAPH500 GENERATES THE GRAPH INSTEAD OF LOADING IT INTO A FILE. GRAPHBIG BUILDS THE GRAPH AND READS IN THE FILE SIMULTANEOUSLY. THESE RESULTS WERE AVERAGED ACROSS 64 ROOTS. [TODO: WHY DOES THE FIRST ROOT OFTEN HAVE DEGREE 0?]

[Compare lines of code for implementation]

VI. GRAPH PROCESSING TAXONOMY

This is in the spirit of [4]. Here, "|" means "or" and "+" means "and." FOSS means Free and Open Source Software. The quotes around "yes" for HPC mean that the product claims to be amenable to high performance computing. Whether these actually achieve their goal is one of the purposes of this project.

VII. CONCLUSION

We have presented an updated survey of parallel graph processing frameworks supplementary to [4]. From this, we have selected a representative subset of frameworks on which performance is analyzed and have stored these results in a database. To facilitate parallel graph processing, hardware information and performance results are automatically populated (as were all the tables in this paper). These performance results are then used to provide simple recommendations of the optimally-performing framework given a particular algorithm and problem size.

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| Name | Type | Parallelism | Target | FOSS | Source | Notes |
|------------|-----------|-------------|---------|------|--------|--------------|
| PowerGraph | Framework | both | CPU | yes | [7] | ^a |
| GraphBIG | Benchmark | shared | CPU GPU | yes | [15] | ^b |
| GAP | Benchmark | shared | CPU | yes | [1] | |
| GraphMat | Framework | shared | CPU | no | [18] | ^c |

TABLE IV
TOOLS USED FOR GRAPH PROCESSING

^aThe current version is a closed-source product by Turi though PowerGraph v2.2 is on Github.

^bOnly works on Linux.

^cRequires the Intel compiler.

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