

# A Comparison of Parallel Graph Processing Platforms

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**Abstract**—This is a survey of existing graph analytics frameworks and an analysis of their performance.

## I. INTRODUCTION

[Talk about WHY we care about graph processing, and parallel in particular. Talk about what parallel graph processing is.]

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 [1]. These systems operate with a wide range of parallelism paradigms such as GPU [Medusa], shared memory [pretty much everything], a combination of CPU and GPU [2], distributed database querying, [3], distributed filesystem based approaches [4], distributed memory with MPI [cite], domain-specific languages [Green Marl], as well as novel communication schemes [activemessages, sockets].

Since 2014, the problem has compounded with the addition of even more proprietary and open source projects such as [5], [6] [name some more]. At the outset, this plethora of choices makes the question, “which system is the best for my problem?” incredibly difficult. There has even been a propagation of so-called “reference implementations” which provide implementations of the most common graph algorithms [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.”

[This paper aims to simplify the selection process for graph processing.]

Another issue with the parallel graph processing library designers is the lack of comprehensive comparison. One possible reason for this is the considerable effort of getting each library and package to work, satisfying dependencies, and ensuring the data is in the correct format for each system. 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 [7] attempts to remedy this but has not seen widespread

adoption—only eight platforms are supported<sup>1</sup>. [TODO: Say more about why this is justified instead of just using Graphalytics]

## II. ALGORITHMS

The canonical performance leaderboard for parallel graph processing is the Graph500 [8]. The advantage of the Graph500 is it provides standardized measurement requirements and dataset generation. The primary drawback with using reference implementations for the Graph500 is the standard only supports 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 [9] 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 BFS<sup>2</sup>. Some clarifications are in order: for the first kernel, the time to read in 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.

## 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 Graph500<sup>3</sup>, GAP [10], and GraphBIG [11].

Parallel Boost Graph Library [12] and PowerGraph [13] implementations are also provided because of their popularity and the availability of high quality reference implementations.

<sup>1</sup>According to <https://github.com/tudelft-atlarge>

<sup>2</sup>For a complete specification, see <http://graph500.org/specifications>

<sup>3</sup>We used version 2.1.4 from <http://graph500.org/referencecode>.

#### 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

	BFS	SSSP	PR
Graph500			
PBGL			
GAP			
GraphBIG			
Galois			
PowerGraph			

TABLE II

PERFORMANCE. NOTE THAT IMPLEMENTATIONS OF EVERY ALGORITHM ARE NOT AVAILABLE FOR EVERY PLATFORM.

Graphalytics without the use of the Granula plugin produces performance measurement in two forms: runtime in seconds and traversed edges per second.

In Table III, 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 [14].

	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 III

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

#### VI. GRAPH PROCESSING TAXONOMY

This is in the spirit of [1]. 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 [1]. 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	HPC	Parallelism	Target	FOSS	Source	Notes
PowerGraph	Framework	“yes”	both	CPU	yes	[13]	<sup>a</sup>
GraphBIG	Benchmark	“yes”	shared	CPU GPU	yes	[11]	<sup>b</sup>

TABLE IV  
TOOLS USED FOR GRAPH PROCESSING

<sup>a</sup>The current version is a closed-source product by Turi though PowerGraph v2.2 is on Github.

<sup>b</sup>Only works on Linux.

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