The GAP Benchmark Suite

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Abstract

We present a graph processing benchmark suite with the goal of helping to standardize graph processing evaluations. Fewer differences between graph processing evaluations will make it easier to compare different research efforts and quantify improvements. The benchmark not only specifies graph kernels, input graphs, and evaluation methodologies, but it also provides optimized baseline implementations. These baseline implementations are representative of state-of-the-art performance, and thus new contributions should outperform them to demonstrate an improvement.

The input graphs are sized appropriately for shared memory platforms, but any implementation on any platform that conforms to the benchmark’s specifications could be compared. This benchmark suite can be used in a variety of settings. Graph framework developers can demonstrate the generality of their programming model by implementing all of the benchmark’s kernels and delivering competitive performance on all of the benchmark’s graphs. Algorithm designers can use the input graphs and the baseline implementations to demonstrate their contribution. Platform designers and performance analysts can use the suite as a workload representative of graph processing.
1 Introduction

Graph algorithms and their application are currently gaining renewed interest. Although the graph abstraction has been around centuries, it has become increasingly relevant, especially as social networks and their analysis grows in importance. Additionally, graph algorithms have found new applications in science and recognition. The result has been renewed interest in supporting graph processing well and for many sizes of graphs. Research is ongoing at all levels, including: applications, algorithms, implementations, frameworks, and even hardware platforms.

A lack of standardization for evaluations has clouded the results from the growing body of graph processing research. To compare a new result to prior work, ideally everything other than the new contribution should be the same. Unfortunately, there is often insufficient overlap between different published results to make such meaningful comparisons. Simple methodology differences (e.g. treating input edges as directed versus undirected) can impact performance more than the claimed improvement. Even for a particular well-known graph problem, there are often many variations (e.g. tracking parent vertices or vertex depth for breadth-first search) that alter what optimizations are possible. The input graphs themselves can be misleading, as similar or identical names can refer to very different input graphs. A standard for graph processing evaluations could combat these sorts of problems.

Other graph processing evaluation mistakes would be harder to make if there is a well-known evaluation standard. With a standard set of diverse input graphs, if an optimization is only compatible with certain topologies, this could be exposed. A standard set of input graphs could also prevent the use of graphs that are trivially small or unrealistically synthetically generated. Standard high-quality reference implementations could help discourage the use of low-performance baselines.

The Graph500 [9] competition has been a great success and we hope to leverage its strengths and expand upon them. Graph500 has strong community adoption that has led to innovation in both algorithms and implementations. For example, the top finisher from the first competition in November 2010 is $5450 \times$ slower than the most recent top finisher, and it would place no higher than 99th in the current rankings (June 2015). The biggest shortcomings of Graph500 is its focus on one kernel (breadth-first search) and only one synthetic input graph topology (Kronecker). Although there are efforts to add additional kernels to Graph500, they are still under review. The Problem-based benchmark suite [19] is another noteworthy effort, but we intend to improve upon it by providing substantially higher performance reference code, using real-world graphs, and focussing on graph algorithms alone.

We present the GAP Benchmark Suite to ameliorate these evaluation concerns. The benchmark suite specifies graph kernels, input graphs, and measurement methodologies. The suite also includes optimized baseline implementations that are representative of state-of-the-art performance.

A key aspect of our benchmark suite is specifying the benchmark itself (this document). Other research efforts have released their code [14, 16, 18, 20] which eases comparisons to themselves, but the evaluator is still responsible for coming up with an evaluation methodology. Furthermore, since these frameworks were developed independently, they may require some modification to ensure the implementations are computing the same thing and using the same timing practices.

Our baseline implementations target shared memory multicore systems, but that platform is not required to use the benchmark suite. The graphs, kernels, and methodologies are of course platform-agnostic. Semi-external memory approaches could demonstrate their competitiveness with shared memory baselines. A distributed graph framework should prove itself worthy of cluster resources.
by substantially outperforming an optimized baseline running on a single node instead of only comparing against itself running on a single node [14].

Note: This is a pre-release of this benchmark. We are providing this early with the hope of helping the community now and encouraging feedback. Both this document as well as the baseline implementations are versioned so future improvements will be clearly labelled.
2 Benchmark Specification

We specify the benchmark by describing:

- Graph kernels and what constitutes a correct solution them
- Input graphs with rationale for their inclusion
- Evaluation methodologies

For clarity, we also include a brief summary of the notation used. A graph $G(V, E)$ is made up by the set of its vertices $V$ and the set of its edges $E$. For conciseness, $n$ and $m$ are used to refer to the number of vertices ($|V|$) and the number of edges ($|E|$). The set of vertices with an edge from vertex $v$ (outgoing neighborhood) is $N^+(v)$ and the set of vertices with an from to vertex $v$ (incoming neighborhood) is $N^-(v)$. If the graph is undirected, both neighborhoods are the same $N^+(v) = N^-(v)$.

2.1 Graph Kernels

We select six kernels based on how commonly they are used and how much diversity they contribute.

- **Breadth-First Search (BFS)** is a traversal order starting from a source vertex. BFS traverses all vertices at the current depth (distance from the source vertex) before moving onto the next depth. BFS is so fundamental, it is often implicit in other graph algorithms. We make BFS into kernel by tracking the parent vertex, akin to Graph500 \[9\]. For any reached vertex, there is often more than one possible parent vertex, as any incoming neighbor with a depth one less than the current vertex could be a legal parent vertex. Because there are multiple legal parent vertices, there is often more than one correct solution to BFS from a given source vertex. For this reason, we specify the requirements for a correct solution of the parent array starting from a source vertex:
  - parent[source] = source
  - parent[x] = -1 if x is unreachable from source
  - if x is reachable and parent[x] = y, there exists an edge from y to x
  - if x is reachable and parent[x] = y, depth[x] = depth[y] + 1

- **Single-Source Shortest Paths (SSSP)** computes the distances to all vertices from a given source vertex. The distance between two vertices is the minimum weight path between the two vertices. Since the solution is the distances and not the shortest paths themselves, there is a unique solution. Although there may be more than one shortest path between two vertices, all shortest paths will have the same distance. All edge weights are positive. We define the correct solution of SSSP to be the distance array from a source vertex such that:
  - distance[source] = 0
  - distance[x] = ”infinity” (some known sentinel value) if x is unreachable from source
  - if x is reachable from source, there is no path of combined weight less than distance[x] from the source to x
• **PageRank (PR)** computes the PageRank score for all vertices in the graph. The score \( PR \) for a vertex \( v \) with a damping factor \( d \) (0.85) is:

\[
PR(v) = \frac{1 - d}{|V|} + d \sum_{u \in N^-(v)} \frac{PR(u)}{|N^+(u)|}
\]

The score is a floating point number, so we use a tolerance bound to define an answer sufficiently close to be considered correct. Under the assumption PageRank is being solved iteratively, we define an answer to be correct if a single additional iteration will change all of the scores by a sum of less than \( 10^{-4} \). We allow for more advanced implementations as long as they meet this bound and any changes to the graph or preprocessing optimizations are counted in the timing. If the benchmark kernel returns scores as \( PR_k \) and an iteration of the classical method uses \( PR_k \) to generate \( PR_{k+1} \), a solution is correct if it obeys the tolerance:

\[
\sum_{v \in V} |PR_k(v) - PR_{k+1}(v)| < 10^{-4}
\]

• **Connected Components (CC)** labels all vertices within the same connected components with the same unique labels. These connected components are of the weak variety, meaning if two vertices are in the same connected component, it is equivalent to there being a path between the two vertices if the graph’s edges are interpreted as undirected. This is in contrast to strongly connected components which requires that if two vertices \( u \) and \( v \) are in the same connected component, there must be a path from \( u \) to \( v \) and a path from \( v \) to \( u \) while respecting the edges’ directions. To define correctness, we require the following equivalence:

- vertices \( u \) and \( v \) have the same component label if and only if there exists an undirected path between \( u \) and \( v \)

• **Betweenness Centrality (BC)** approximates the betweenness centrality score for all vertices in the graph by only computing the shortest paths from a subset of all of the vertices. These centrality scores should be normalized to one. The betweenness centrality of a vertex \( v \) is defined to be the fraction of shortest paths that pass through. If \( \sigma_{st} \) is the number of shortest paths between vertices \( s \) and \( t \) and \( \sigma_{st}(v) \) is the number of those shortest paths that pass through \( v \), the betweenness centrality score for \( v \) is:

\[
BC(v) = \sum_{s,t \in V, s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}
\]

We establish correctness by comparing to a simple correct implementation using the same source vertices.

• **Triangle Counting (TC)** returns the total number of triangles in an undirected graph. If the graph is directed, it should be interpreted as an undirected graph. A triangle is a clique of size 3, that is three vertices \( u, v, w \) that are all directly connected to each other. A triangle is invariant to permutation, so the same three vertices can be counted for only one triangle no matter the order in which they are listed.
2.2 Input Graphs

We select five input graphs to be both diverse in topology and origin (synthetic versus real-world). These graph sizes are selected to be small enough to fit comfortably in most servers’ memory yet large enough to be orders of magnitude bigger than the processors’ caches. We also consider the ease of users acquiring real-world benchmark graphs, and the graphs selected were amongst the easiest to obtain (licensing and bandwidth).

- **Twitter** ($|V|=61.6M$, $|E|=1,468.4M$, directed) is an example of a social network topology [10]. This particular crawl of Twitter has been heavily used by researchers and thus eases comparisons with prior work.

- **Web** ($|V|=50.6M$, $|E|=1,949.4M$, directed) is a web-crawl of the .sk domain (sk-2005) [5]. Despite its large size, it exhibits substantial locality due to its topology and high average degree.

- **Road** ($|V|=23.9M$, $|E|=58.3M$, directed) is all of the roads in the USA [6]. Although it is substantially smaller than the rest of the graphs, it has a high diameter which can cause some synchronous algorithms to have long runtimes.

- **Kron** ($|V|=128.0M$, $|E|=2,048.0M$, undirected) uses the Kronecker synthetic graph generator [11] with the same parameters as Graph500 ($A=0.57$, $B=C=0.19$, $D=0.05$) [9]. It has been used heavily in research due to Graph500, so it also provides continuity with prior work.

- **Uniform** ($|V|=128.0M$, $|E|=2,048.0M$, undirected) is synthetically generated by the Erdős–Réyni model (Uniform Random) [7]. With respect to locality, it represents the worst case as every vertex has equal probability of being neighbors with every other vertex.

All of the graphs except road are unweighted, so weights must be added to them before executing SSSP. Weights should be integers uniformly distributed amongst $[1,255]$, and we recommend using the reference code for this as it is deterministic.

2.3 Measurement Methodologies

Given the input graphs and kernels, we now specify the measurement methodologies each with a bit of rationale. Building on the success of Graph500 [9], we reuse many of its best practices.

Executing only a subset of the benchmark kernels is allowed, as some users of this suite may only be investigating a single graph problem. However, it is highly recommended to always use all of the input graphs as they are selected to be diverse. New innovations may not work well for all input graphs, so it is important to understand the topologies for which the innovation is advantageous.

There are no restrictions on the layout of the graph in memory, however, the same graph layout must be used for all kernels. Any optimizations done to the graph layout must not be beneficial to only one algorithm. It is legal to remove duplicate edges and self-loops from the graph. It is also legal to reorder the neighbors of a vertex. If the graph is relabelled, outputs of the graph kernel must use the original vertex labels and this conversion time should be included in the kernel time.

We select the number of trials each kernel should run with the goal of minimizing measurement time while capturing enough samples to return significant results. In general, the kernels can be
grouped into two classes: "single-source" kernels take a source vertex to start from and "whole-
graph" kernels process the entire graph every time in the same way. For single-source kernels, there
is naturally substantial variation in execution time so we execute 64 trials each from a different
source vertex. The source vertices are randomly selected non-zero degree vertices from the graph
and we recommend the vertex selector from the reference code as it is deterministic. For the whole-
graph kernels, we execute just enough trials to capture any performance non-determinism. The
trial counts are summarized in Table 1.

Each trial of a kernel should be timed individually and it should include every aspect of its exe-
cution. Any time to construct data structures (other than the graph) used by the kernel (including
memory allocated for the solution) must be included in the trial time. Additionally, the graph is
the only data structure that can be reused between trials, as the purpose of repeated trials is to
measure variance, not to amortize optimizations.

For each kernel, there must be only one implementation used for all input graphs. If different
approaches will be better for different graph topologies, they should be combined into a hybrid
approach which includes a runtime heuristic (included in kernel time) to decide which approach to
use. The same restriction applies to tuning parameters. None of the kernels may take parameters
specific to the input graph with the exception of a $\Delta$ parameter for SSSP. A kernel can take tuning
parameters specific to the hardware platform that will be the same for all input graphs.

The benchmark allows for the use of 32-bit words, but the implementations must support graphs
with more than $2^{32}$ edges. The particular output formats are summarized in Table 1.

| Kernel | Trials | Output |
|--------|--------|--------|
| BFS    | 64 trials from 64 sources | $|V|$-sized array of 32-bit integers (vertex identifiers) |
| SSSP   | 64 trials from 64 sources | $|V|$-sized array of 32-bit integers (distances) |
| BC     | 16 trials each from 4 sources | $|V|$-sized array of 32-bit floating point numbers |
| PR     | 16 trials | $|V|$-sized array of 32-bit floating point numbers |
| CC     | 16 trials | $|V|$-sized array of 32-bit integers (component labels) |
| TC     | 3 trials | 64-bit integer (number of triangles) |

Table 1: Trial counts and outputs
3 Reference Code

The baseline implementations we provide serve multiple purposes. They are not only intended to demonstrate leading performance, but they can also be used as a references for how to implement some state-of-the-art algorithms or even as starting points for future implementations. To serve these other purposes, extra effort has been taken to improve code quality. Our code leverages many of the features of C++11 that allow us to program safer without any loss of performance. For example, the kernel implementations and most of the core infrastructure do not perform manual memory management or even use pointers. For parallelism, we leverage OpenMP and restrict ourselves to its simpler features in order to keep our code portable. We have successfully built and run our code on the x86_64, ARMv7, and RISC-V ISA’s with the gcc, clang, and icc compilers.

The core infrastructure for our reference code includes support for synthetically generating graphs, loading graphs from files, and building graphs in memory. We support a few file formats, including very simple plain text formats to make it easy for others to convert other graphs into formats readable by our implementations. Once our code has built a graph, it can serialize it to a file so later invocations can simply load the serialized graph to save time and reduce peak memory consumption by skipping graph building. The synthetic graph generators take advantage of C++11’s strict random number generator specifications and seeding to deterministically produce the same graph in parallel even on different platforms or with different numbers of threads.

Our reference code also includes testing throughout. In addition to testing the code for loading a graph from a file, generating a graph synthetically, or building a graph in memory, our code verifies the outputs of the graph kernels are correct. When possible, our verifiers test the kernel output for certain properties, especially when there is more than one correct solution (BFS, PR, CC). For the other kernels (SSSP, BC, TC), we compare the output to the output from a trivially simple serial baseline that implements the kernel with a different algorithm.

Here we describe some of the most noteworthy or novel optimizations employed by our kernel implementations, but we of course recommend examining the code itself [8] to answer detailed questions.

- **Breadth-First Search (BFS)** implements the current state-of-the-art direction-optimizing algorithm [2]. We perform an additional optimization to reduce the amount of time spent calculating how many edges exit the current frontier. Calculating the number of edges in the frontier is done during the top-down steps to determine if the frontier is large enough to justify switching to the bottom-up approach. Computing this total can have many irregular accesses, as it is summing the degrees of an unordered list of vertices. Our optimization is to add a step before the search that stores the degree of each vertex in the parent array as a negative number and this takes little time as the vertices can be done in order (great spatial locality). The previous convention of -1 representing an unvisited vertex is now revised to be any negative number represents an unvisited vertex. With this new encoding, during the top-down steps the degree of a newly reached vertex is already known because the parent array was just checked to see if that vertex was unvisited. This optimization cuts out totaling the degrees of the frontier because it can now be done during the search. For low-diameter graphs, this yields a modest performance improvement, but for high-diameter graphs that will only use the top-down approach, this can yield a speedup of nearly 2×.

To verify the BFS output, we test for the properties specified in the BFS specification. We check that the parent of the source is the source. We check that if there is an edge from
the parent of v to v. We use a trivial serial BFS implementation to obtain the depths of all vertices from the source, and with that we also check that the depth of the parent of v is one less than the depth of v.

- **Single-Source Shortest Paths (SSSP)** implements the Δ-stepping algorithm [15] with some implementation optimizations from Madduri et al. [12]. Rather than having the bins shared across all threads and dealing with concurrent appends, we use thread local bins. One of the challenges involved with shared bins is that it is complicated to grow concurrent bins and if they are sized large enough to not need to grow, there is the possibility of substantially wasted memory capacity. With thread local bins, for each iteration a single shared bin is aggregated from the thread local bins for that distance. Since the bins are thread local, we can use existing resizable containers (std::vector). This optimization greatly simplifies the implementation as there are no longer parameters to tune for bin size or the number of bins to pre-allocate.

To verify the output of SSSP, we compare it to the output of a simple serial implementation of Dijkstra’s algorithm.

- **PageRank (PR)** uses the naive iterative approach that is quite similar to sparse matrix vector multiplication (SpMV). To avoid the use of atomic memory operations, we perform all updates in the pull-direction. Unlike the rest of our implementations, we deliberately chose to not implement the most sophisticated state-of-the-art algorithm in order to be easily comparable. PageRank is the most commonly used benchmark, and most often it is implemented in this same classical way, so these implementations can be directly compared since they perform the same amount of algorithmic work. Many optimizations not only change the algorithmic amount of work, but in actuality do not obtain the tolerance bounds they advertise. Our benchmark allows for optimized PageRank implementations, but they must meet the tolerance bounds.

We verify the output of PR, by summing the changes of an additional iteration. Our verifier’s implementation is serial and performs updates in the push direction.

- **Connected Components (CC)** implements the Shiloach-Vishkin [17] algorithm with parallelization techniques from Bader et al. [1].

We verify the output of CC by checking for the equivalence stated in the CC specification. We do this by performing a traversal from a vertex with each label. During that traversal, it is checked that a different label is not encountered. At the end of all these traversals, we assert that every non-zero degree vertex has been reached by a traversal, because if two components share the same label it would result in unreached vertices.

- **Betweenness Centrality (BC)** implements the Brandes [3] algorithm with the lock-free improvements from Madduri et al. [13]. To obtain a slight speedup and a large memory savings, we record the successors identified during the BFS pass in a bitmap rather than many lists whose total capacity is $O(|E|)$.

We verify the output of BC by comparing it to the output from a simple serial implementation. Our verifier implementation also uses Brandes algorithm, however, it is implemented in a different way and it does not cache the successors during the BFS pass.
Triangle Counting (TC) implements two well-known optimizations [4]. To count triangles, we sum the sizes of the overlap between a vertex’s neighbor list and its neighbors’ neighbor lists. Our first optimization leverages our neighbor lists being ordered and terminates these intersection checks once the triangles found will obey the invariant of \( u > v > w \). Our second optimization relabels the graph by degree, so when the first ordering optimization is applied, we get additional algorithmic savings. Relabelling the graph is compute-intensive, but counting triangles exactly is also compute-intensive so the relabelling optimization can often be amortized. To determine if relabelling will be worthwhile, we use the heuristic of if the graph has a sufficiently high average degree and if the degree distribution is sufficiently skewed (sample median degree < average degree).

We verify the count from TC by comparing it the count returned by a trivial serial implementation leveraging \texttt{std::set\_intersection}.
A Change Log

Changes since v1

- Benchmark Specification: converted trials and output into table format
- Reference Code: description of testing and verifier implementations
- Reference Code: move to version v0.7 in GitHub repo
- Acknowledgements: added section
- General wording and grammar fixes throughout

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