GPS: A Graph Processing System[*]

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Abstract

GPS (for Graph Processing System) is a complete open-source system we developed for scalable, fault-tolerant, and easy-to-program execution of algorithms on extremely large graphs. This paper serves the dual role of describing the GPS system, and presenting techniques and experimental results for graph partitioning in distributed graph-processing systems like GPS. GPS is similar to Google's proprietary Pregel system, with three new features: (1) an extended API to make global computations more easily expressed and more efficient; (2) a dynamic repartitioning scheme that reassigns vertices to different workers during the computation, based on messaging patterns; and (3) an optimization that distributes adjacency lists of high-degree vertices across all compute nodes to improve performance. In addition to presenting the implementation of GPS and its novel features, we also present experimental results on the performance effects of both static and dynamic graph partitioning schemes.

1 Introduction

Building systems that process vast amounts of data has been made simpler by the introduction of the *MapReduce* framework [DG04], and its open-source implementation *Hadoop* [HAD]. These systems offer automatic scalability to extreme volumes of data, automatic fault-tolerance, and a simple programming interface based around implementing a set of

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functions. However, it has been recognized [MAB$^+$11, LGK$^+$10] that these systems are not always suitable when processing data in the form of a large graph (details in Section 6). A framework similar to MapReduce—scalable, fault-tolerant, easy to program—but geared specifically towards graph data, would be of immense use. Google's proprietary *Pregel* system [MAB$^+$11] was developed for this purpose. Pregel is a *distributed message-passing system*, in which the vertices of the graph are distributed across compute nodes and send each other messages to perform the computation. We have implemented a robust open-source system called *GPS*, for *Graph Processing System*, which has drawn from Google's Pregel.

In addition to being open-source, GPS has three new features that do not exist in Pregel, nor in an alternative open-source system *Giraph* [GIR] (discussed further in Section 5):

1. Only "vertex-centric" algorithms can be implemented easily and efficiently with the Pregel API. The GPS API has an extension that enables efficient implementation of algorithms composed of one or more vertex-centric computations, combined with global computations.

2. Unlike Pregel, GPS can repartition the graph dynamically across compute nodes during the computation, to reduce communication.

3. GPS has an optimization called *large adjacency list partitioning (LALP)*, which partitions the adjacency lists of high-degree vertices across compute nodes, again to reduce communication.

Next we explain the computational framework used by Pregel and GPS. Then we motivate GPS's new features. Finally we outline the second contribution of this paper: experiments demonstrating how different ways of partitioning, and possibly repartitioning, graphs across compute nodes affects the performance of algorithms running on GPS.

1.1 Bulk Synchronous Graph Processing

The computational framework introduced by Pregel and used by GPS is based on the *Bulk Synchronous Parallel (BSP)* computation model [Val90]. At the beginning of the computation, the vertices of the graph are distributed across compute nodes. Computation consists of iterations called *supersteps*. In each superstep, analogous to the *map()* and *reduce()* functions in the MapReduce framework, a user-specified *vertex.compute()* function is applied to each vertex in parallel. Inside *vertex.compute()*, the vertices update their state information (perhaps based on incoming messages), send other vertices messages to be used in the next iteration, and set a flag indicating whether this vertex is ready to stop computation. At the end of each superstep, all compute nodes synchronize before starting the next superstep. The iterations stop when all vertices vote to stop computation. Compared to Hadoop, this model is more suitable for graph computations since it is inherently iterative and the graph can remain in memory throughout the computation. We compare this model to Hadoop-based systems in more detail in Section 6.

1.2 Master.compute()

Implementing a graph computation inside *vertex.compute()* is ideal for certain algorithms, such as computing PageRank [BP98], finding shortest paths, or finding connected components, all of which can be performed in a fully "vertex-centric" and hence parallel fashion. However, some algorithms are a combination of vertex-centric (parallel) and global (sequential) computations. As an example, consider the following k-means-like graph clustering algorithm that consists of four parts: (a) pick k random vertices as "cluster centers", a computation global to the entire graph; (b) assign each vertex to a cluster center, a vertex-centric computation; (c) assess the goodness of the clusters by counting the number of edges crossing clusters, a vertex-centric computation; (d) decide whether to stop, if the clustering is good enough, or go back to (a), a global computation. We can implement global computations inside *vertex.compute()* by designating a "master" vertex to run them. However, this approach has two problems: (1) The master vertex executes each global computation in a superstep in which all other vertices are idle, wasting resources. (2) The *vertex.compute()* code becomes harder to understand, since it contains some sections that are written for all vertices and others that are written for the special vertex. To incorporate global computations easily and efficiently, GPS extends the API of Pregel with an additional function, *master.compute()*, explained in detail in Section 2.4.

1.3 GPS's Partitioning Features

In GPS, as in Pregel, messages between vertices residing in different compute nodes are sent over the network. The two new features of GPS in addition to *master.compute()* are designed to reduce the network I/O resulting from such messages. First, GPS can optionally repartition the vertices of the graph across compute nodes automatically during the computation, based on their message-sending patterns. GPS attempts to colocate vertices that send each other messages frequently. Second, in many graph algorithms, such as PageRank and finding connected components, each vertex sends the same message to all of its neighbors. If, for example, a high-degree vertex v on compute node i has 1000 neighbors on compute node j, then v sends the same message 1000 times between compute nodes i and j. Instead, GPS's *LALP* optimization (explained in Section 3.4) stores partitioned adjacency lists for high-degree vertices across the compute nodes on which the neighbors reside. In our example, the 1000 messages are reduced to one.

1.4 Partitioning Experiments

By default GPS and Pregel distribute the vertices of a graph to the compute nodes randomly (typically round-robin). Using GPS we have explored the *graph partitioning* question: Can some algorithms perform better if we "intelligently" assign vertices to compute nodes before the computation begins? For example, how would the performance of the PageRank algorithm change if we partition the web-pages according to their domains, i.e., if all web-pages with the same domain names reside on the same compute node? What happens if we use the popular METIS [MET] algorithm for partitioning, before computing PageRank, shortest-path, or other algorithms? Do we improve performance further by using GPS's dynamic repartitioning scheme? We present extensive experiments demonstrating that the answer to all of these questions is yes, in certain settings. We will also see that maintaining workload balance across compute nodes, when using a sophisticated partitioning scheme, is nontrivial to achieve but crucial to achieving good performance.

1.5 Contributions and Paper Outline

The specific contributions of this paper are as follows:

- In Section 2, we present GPS, our open-source Pregel-like distributed message passing system for large-scale graph algorithms. We present the architecture and the programming API.
- In Section 3, we study how different graph partitioning schemes affect the network and run-time performance of GPS on a variety of graphs and algorithms. We repeat some of our experiments using *Giraph* [GIR], another open-source system based on Pregel, and report the results. We also describe our large adjacency-list partitioning feature (LALP) and report some experiments on it.

- In Section 4, we describe GPS's dynamic repartitioning scheme. We repeat several of our experiments from Section 3 using dynamic repartitioning.
- We finish in Section 5 by discussing several additional optimizations that reduce memory use and increase the overall speed of GPS.

Section 6 discusses related work and Section 7 concludes and proposes future work.

2 GPS System

GPS uses the distributed message-passing model of Pregel [MAB+11], which is based on bulk synchronous processing [Val90]. We give an overview of the model here and refer the reader to [MAB+11] for details. Broadly, the input is a directed graph, and each vertex of the graph maintains a user-defined *value*, and a *flag* indicating whether or not the vertex is active. Optionally, edges may also have values. The computation proceeds in iterations called *supersteps*, terminating when all vertices are inactive. Within a superstep i, each active vertex u in parallel: (a) looks at the messages that were sent to u in superstep $i-1$; (b) modifies its value; (c) sends messages to other vertices in the graph and optionally becomes inactive. A message sent in superstep i from vertex u to vertex v becomes available for v to use in superstep $i+1$. The behavior of each vertex is encapsulated in a function *vertex.compute()*, which is executed exactly once in each superstep.

2.1 Overall Architecture

The architecture of GPS is shown in Figure 1. As in Pregel, there are two types of *processing elements (PEs)*: one master and k workers, $W_0 ... W_{k-1}$. The master maintains a mapping of PE identifiers to physical compute nodes and workers use a copy of this mapping to communicate with each other and the master. PEs communicate using Apache MINA ["ZM], a network application framework built on java.nio, Java's asynchronous network I/O package. GPS is implemented in Java. The compute nodes run *HDFS (Hadoop Distributed File System)* [HDF], which is used to store persistent data such as the input graph and the checkpointing files. We next explain how the input graph is partitioned across workers. The master and worker implementations are described in Section 2.3. Section 2.4 explains the API and provides examples.

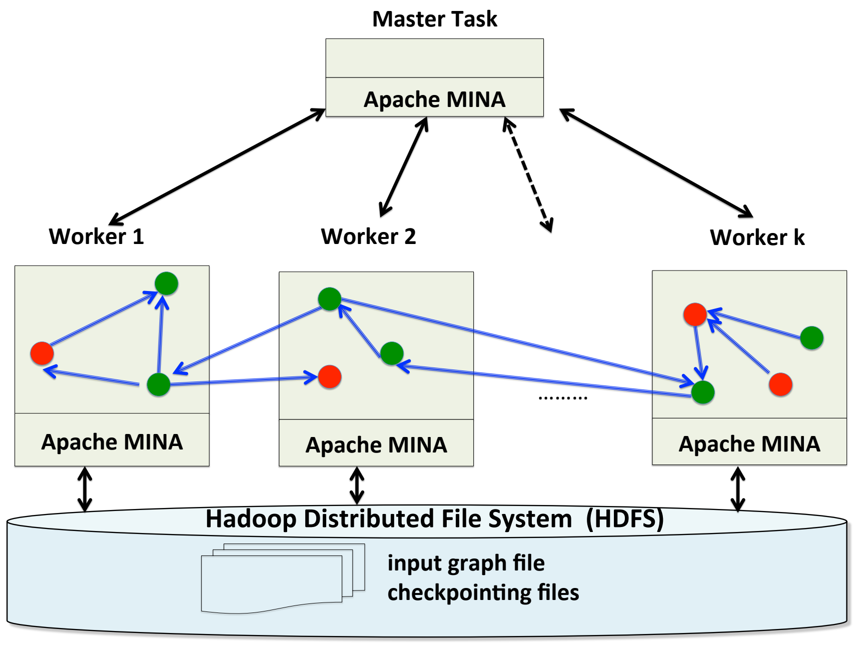


Figure 1: GPS Architecture

2.2 Input Graph Partitioning Across Workers

The input graph G is specified in HDFS files in a simple format: each line starts with the ID of a vertex u, followed by the IDs of u's outgoing neighbors. The input file may optionally specify values for the vertices and edges. GPS assigns the vertices of G to workers using the same simple round-robin scheme used by Pregel: vertex u is assigned to worker $W_{(u \mod k)}$. When we experiment with more sophisticated partitioning schemes (Section 3), we run a preprocessing step to assign node IDs so that the round-robin distribution reflects our desired partitioning. GPS also supports optionally repartitioning the graph across workers during the computation, described in Section 4.

2.3 Master and Worker Implementation

The master and worker PEs are again similar to Pregel [MAB$^+$11]. The master coordinates the computation by instructing workers to: (a) start parsing input files; (b) start a new superstep; (c) terminate computation; and (d) checkpoint their states for fault-tolerance. The master awaits notifications from all workers before instructing workers what to do next, and so serves as the centralized location where workers synchronize between supersteps. The master also calls a *master.compute()* function at the beginning of each superstep, described in Section 2.4.

Workers store vertex values, active flags, and *message queues* for the current and next supersteps. Each worker consists of three "thread groups", as follows.

1. A *computation thread* loops through the vertices in the worker and executes *vertex.compute()* on each active vertex. It maintains an outgoing *message buffer* for all workers in the cluster, including itself. When a buffer is full it is either given to *MINA threads* for sending over the network, or passed directly to the local *message parser thread*.

2. *MINA threads* send and receive message buffers, as well as simple *coordination messages* between the master and the worker. When a message buffer is received, it is passed to the message parser thread.

3. A *message parser thread* parses incoming message buffers into separate messages and enqueues them into the receiving vertices' message queues for the next superstep.

One advantage of this thread structure is that there are only two lightweight points of synchronization: when the computation thread passes a message buffer directly to the message parser thread, and when a MINA thread passes a message buffer to the message parser thread. Since message buffers are large (the default size is 100KB), these synchronizations happen infrequently.

2.4 API

Similar to Pregel, the programmer of GPS subclasses the *Vertex* class to define the vertex value, message, and optionally edge-value types. The programmer codes the vertex-centric logic of the computation by implementing the *vertex.compute()* function. Inside *vertex.compute()*, vertices can access their values, their incoming messages, and a map of *global objects*—our implementation of the *aggregators* of Pregel. Global objects are used for coordination, data sharing, and statistics aggregation. At the beginning of each superstep, each worker has the same copy of the map of global objects. During a superstep, vertices can update objects in their worker's local map, which are merged at the master at the end of the superstep, using a user-specified merge function. When ready, a vertex declares itself inactive by calling the *voteToHalt()* function in the API.

Algorithms whose computation can be expressed in a fully vertex-centric fashion are easily implemented using this API, as in our first example.

```
class HCCVertex extends Vertex<IntWritable, IntWritable> {
  @Override
   void compute(Iterable<IntWritable> messages,
                 int superstepNo) {
    if (superstepNo == 1) {
      setValue(new IntWritable(getId()));
      sendMessages(getNeighborIds(), getValue());
    } else {
      int minValue = getValue().value();
      for (IntWritable message : messages) {
        if (message.value() < minValue) {
          minValue = message.value(); }}
      if (minValue < getValue().value()) {
        setValue(new IntWritable(minValue));
        sendMessages(getNeighborIds(), getValue());
      } else {
        voteToHalt(); }}}}
```

Figure 2: Connected components in GPS.

```
1 Input: undirected G(V, E), k, τ
2  int numEdgesCrossing = INF;
3  while (numEdgesCrossing > τ)
4    int[] clusterCenters = pickKRandomClusterCenters(G)
5    assignEachVertexToClosestClusterCenter(G, clusterCenters)
6    numEdgesCrossing = countNumEdgesCrossingClusters(G)
```

Figure 3: A simple k-means like graph clustering algorithm.

Example 2.1 *HCC* [KTF09] is an algorithm to find the weakly connected components of an undirected graph: First, every vertex sets its value to its own ID. Then, in iterations, vertices set their values to the minimum value among their neighbors and their current value. When the vertex values converge, the value of every vertex v is the ID of the vertex that has the smallest ID in the component that v belongs to; these values identify the weakly connected components. HCC can be implemented easily using *vertex.compute()*, as shown in Figure 2. □

A problem with this API (as presented so far) is that it is difficult to implement algorithms that include global as well as vertex-centric computations, as shown in the following example.

Example 2.2 Consider the simple k-means like graph clustering algorithm introduced in Section 1 and outlined in Figure 3. This algorithm has two vertex-centric parts:

1. Assigning each vertex to the closest "cluster center" (line 5 in Figure 3). This process

```
public class ClusteringVertex extends Vertex<TwoIntWritable, TwoIntWritable> {
  @Override
  public void compute(Iterable<TwoIntWritable> messages, int superstepNo){
    if (superstepNo == 1) {
      Set<Integer> clusterCenters = getGlobalObjects("cluster-centers");
      setValue(clusterCenters.contains(getId()) ?
        new TwoIntWritable(0, getId()) :
          new TwoIntWritable(Integer.MAX_VALUE, null));
      if (clusterCenters.contains(getId())) {
        sendMessages(getNeighborIds(), getValue());}
    } else {
      int minDistance = getValue().value().fst;
      int minDistanceClusterId = getValue().value().snd;
      for (TwoIntWritable message : messages) {
        if (message.value().fst  < minValue) {
          minValue = message.value();
          minDistanceClusterId = message().value().snd;}}
      if (minDistance < getValue().value().fst) {
        setValue(new TwoIntWritable(minDistance, minDistanceClusterId));
        sendMessages(getNeighborIds(), getValue());
      } else {
        voteToHalt(); }}}}
```

Figure 4: Assigning each vertex to the closest cluster with *vertex.compute()*.

is a simple extension of the algorithm from [MAB+11] to find shortest paths from a single source and is shown in Figure 4.

2. Counting the number of edges crossing clusters (line 6 in Figure 3). This computation requires two supersteps; it is shown in Figure 5.

Now consider lines 2 and 3 in Figure 3: checking the result of the latest clustering and terminating if the threshold has been met, or picking new cluster centers. With the API so far, we must put this logic inside *vertex.compute()* and designate a special *"master"* vertex to do it. Therefore, an entire extra superstep is spent at each iteration of the while loop (line 3 in Figure 3) to do this very short computation at one vertex, with others idle. Global objects cannot help us with this computation, since they only store values. □

In GPS, we have addressed the shortcoming illustrated in Example 2.2 by extending the Pregel API to include an additional function, *master.compute()*. The programmer subclasses the *Master* class, and implements the *master.compute()* function, which gets called at the beginning of each superstep. The *Master* class has access to all of the merged global objects, and it can store its own global data that is not visible to the vertices. It can update the global objects map before it is broadcast to the workers.

```
public class EdgeCountingVertex extends Vertex<IntWritable, IntWritable> {
  @Override
  public void compute(Iterable<IntWritable> messages, int superstepNo){
    if (superstepNo == 1) {
      sendMessages(getNeighborIds(), getValue().value());
    } else if (superstepNo == 2) {
      for (IntWritable message : messages) {
        if (message.value() != getValue().value()) {
          minValue = message.value();
          updateGlobalObject("num-edges-crossing-clusters",
            new IntWritable(1));}}
      voteToHalt(); }}}
```

Figure 5: Counting the number of edges crossing clusters with *vertex.compute()*.

Figure 6 shows an example *master.compute()*, used together with the vertex-centric computations already described (encapsulated in *SimpleClusteringVertex*, not shown) to implement the overall clustering algorithm of Figure 3. Lines 2 and 3 in Figure 3 are implemented in lines 24 and 25 of Figure 6. *SimpleClusteringMaster* maintains a global object, *comp-stage*, that coordinates the different stages of the algorithm. Using this global object, the master signals the vertices what stage of the algorithm they are currently in. By looking at the value of this object, vertices know what computation to do and what types of messages to send and receive. Thus, we are able to encapsulate vertex-centric computations in *vertex.compute()*, and coordinate them globally with *master.compute()*.

3 Static Graph Partitioning

We next present our experiments on different static partitionings of the graph. In Section 3.2 we show that by partitioning large graphs "intelligently" before computation begins, we can reduce total network I/O by up to 13.6x and run-time by up to 2.5x. The effects of partitioning depend on three factors: (1) the graph algorithm being executed; (2) the graph itself; and (3) the configuration of the worker tasks across compute nodes. We show experiments for a variety of settings demonstrating the importance of all three factors. We also explore partitioning the adjacency lists of high-degree vertices across workers. We report on those performance improvements in Section 3.4. Section 3.1 explains our experimental set-up, and Section 3.3 repeats some of our experiments on the *Giraph* open-source graph processing system.

```
public class SimpleClusteringMaster extends Master {
  @Override
  public void compute(int nextSuperstepNo) {
    if (nextSuperstepNo == 1) {
      pickKVerticesAndPutIntoGlobalObjects();
      getGlobalObjects().put("comp-stage",
        new IntGlobalObject(CompStage.CLUSTER_FINDING_1));
    } else {
      int compStage = getGlobalObject("comp-stage").value();
      switch(compStage) {
      case CompStage.CLUSTER_FINDING_1:
        getGlobalObjects().put("comp-stage",
          new IntGlobalObject(CompStage.CLUSTER_FINDING_2));
      break;
      case CompStage.CLUSTER_FINDING_2:
        if (numActiveVertices() == 0) {
          getGlobalObjects().put("comp-stage",
            new IntGlobalObject(CompStage.EDGE_COUNTING_1));}
      break;
      case CompStage.EDGE_COUNTING_1:
        getGlobalObjects().put("comp-stage",
          new IntGlobalObject(CompStage.EDGE_COUNTING_2));
      break;
      case CompStage.EDGE_COUNTING_2:
        int numEdgesCrossing = getGlobalObject("num-edges-crossing").value();
        if (numEdgesCrossing > threshold) {
          pickKVerticesAndPutIntoGlobalObjects();
          getGlobalObjects().put("comp-stage",
            new IntGlobalObject(CompStage.CLUSTER_FINDING_1));
        } else {
          terminateComputation(); }}}}
```

Figure 6: Clustering algorithm using *master.compute()*.

3.1 Experimental Setup

We describe our computing set-up, the graphs we use, the partitioning algorithms, and the graph algorithms used for our experiments.

We ran all our experiments on the Amazon EC2 cluster using large instances (4 virtual cores and 7.5GB of RAM) running Red Hat Linux OS. We repeated each experiment five times with checkpointing turned off. The numeric results we present are the averages across all runs ignoring the initial data loading stage. Performance across multiple runs varied by only a very small margin.

The graphs we used in our experiments are specified in Table 1.[1] We consider four

[1]These datasets were provided by "The Labaratory for Web Algorithmics" [LAW], using software packages WebGraph [BV04], LLP [BRSV11] and UbiCrawler [BCSV04].

Name	Vertices	Edges	Description
uk-2007-d	106M	3.7B	web graph of the .uk domain from 2007 (directed)
uk-2007-u	106M	6.6B	undirected version of uk-2007-d
sk-2005-d	51M	1.9B	web graph of the .sk domain from 2005 (directed)
sk-2005-u	51M	3.2B	undirected version of sk-2005-d
twitter-d	42M	1.5B	Twitter "who is followed by who" network (directed)
uk-2005-d	39M	750M	web graph of the .uk domain from 2005 (directed)
uk-2005-u	39M	1.5B	undirected version of uk-2005-d

Table 1: Data sets.

different static partitionings of the graphs:

- *Random*: The default "mod" partitioning method described in Section 2, with vertex IDs ensured to be random.
- *METIS-default*: METIS [MET] is publicly-available software that divides a graph into a specified number of partitions, trying to minimize the number of edges crossing the partitions. By default METIS balances the number of vertices in each partition. We set the *ufactor* parameter to 5, resulting in at most 0.5% imbalance in the number of vertices assigned to each partition [MET].
- *METIS-balanced*: Using METIS' multi-constraint partitioning feature [MET], we generate partitions in which the number of vertices, outgoing edges, and incoming edges of partitions are balanced. We again allow 0.5% imbalance in each of these constraints. METIS-balanced takes more time to compute than METIS-default, although partitioning time itself is not a focus of our study.
- *Domain-based*: In this partitioning scheme for web graphs only, we locate all web pages from the same domain in the same partition, and partition the domains randomly across the workers.

Unless stated otherwise, we always generate the same number of partitions as we have workers.

Note that we are assuming an environment in which partitioning occurs once, while graph algorithms may be run many times, therefore we focus our experiments on the effect partitioning has on algorithms, not on the cost of partitioning itself.

We use four different graph algorithms in our experiments:

- *PageRank (PR)* [BP98]
- Finding shortest paths from a single source *(SSSP)*, as implemented in [MAB+11]

- The *HCC* [KTF09] algorithm to find connected components
- *RW-n*, a pure random-walk simulation algorithm. Each vertex starts with an initial number of n walkers. For each walker i on a vertex u, u randomly picks one of its neighbors, say v, to simulate i's next step. For each neighbor v of u, u sends a message to v indicating the number of walkers that walked from u to v.

3.2 Performance Effects of Partitioning

Because of their bulk synchronous nature, the speed of systems like Pregel, GPS, and Giraph is determined by the slowest worker to reach the synchronization points between supersteps. We can break down the workload of a worker into three parts:

1. *Computation*: Looping through vertices and executing *vertex.compute()*
2. *Networking*: Sending and receiving messages between workers
3. *Parsing and enqueuing messages*: In our implementation, where messages are stored as raw bytes, this involves byte array allocations and copying between byte arrays.

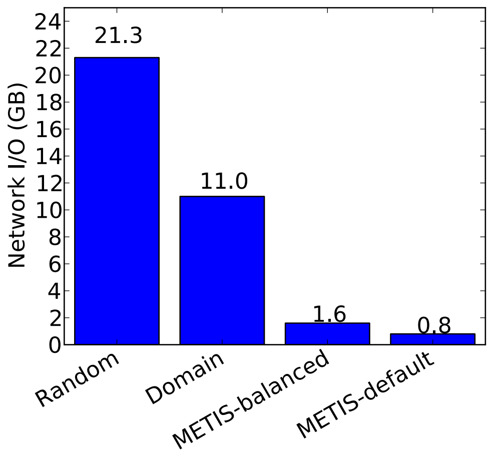
Although random partitioning generates well-balanced workloads across workers, almost all messages are sent across the network. We show that we can both maintain a balanced workload across workers and significantly reduce the network messages and overall run-time by partitioning the graph using our more sophisticated schemes.

With sophisticated partitioning of the graph we can obviously reduce network I/O, since we localize more edges within each worker compared to random partitioning. Our first set of experiments, presented in Section 3.2.1, quantifies the network I/O reduction for a variety of settings.

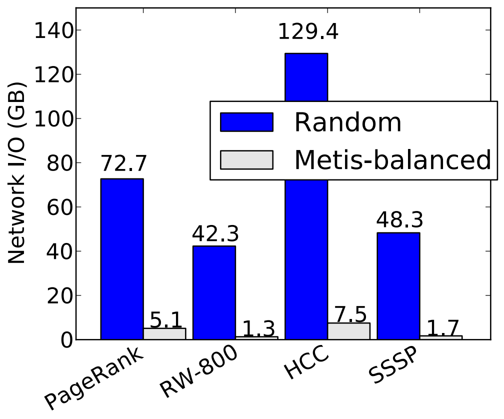
In Section 3.2.2, we present experiments measuring the run-time reduction due to sophisticated partitioning when running various algorithms in a variety of settings. We observe that partitioning schemes that maintain workload balance among workers perform better than schemes that do not, even if the latter have somewhat lower communication. In Section 3.2.3, we discuss how to fix the workload imbalance among workers when a partitioning scheme generates imbalanced partitions.

3.2.1 Network I/O

In our first set of experiments, we measured network I/O (network writes in GB across all workers) when running different graph algorithms under different partitioning schemes in



(a) *PageRank on sk-2005-d*



(b) *Different algorithms on uk-2007-u*

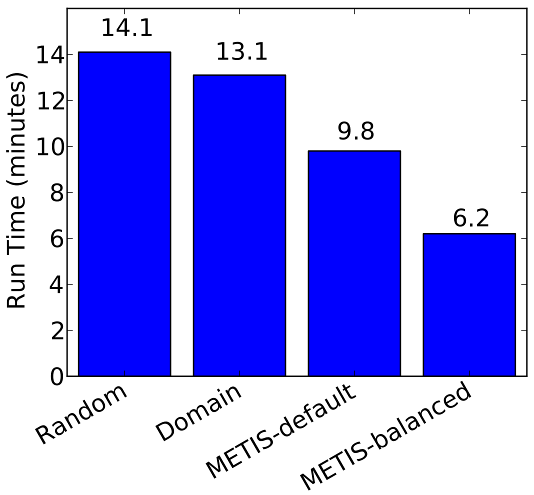
Figure 7: Network I/O, different partitioning schemes

a variety of settings. The reductions we report are relative to the performance of random partitioning. Overall, network I/O reductions varied between 1.8x to 2.2x for partitioning by domain, 13.3x and 36.3x for METIS-balanced, and 26.6x and 58.5x for METIS-default. We present two of our experiments in Figure 7. Figure 7a shows network I/O for different partitioning schemes when running PageRank on the *sk-2005-d* graph (recall Table 1), with 60 workers running on 60 compute nodes. Figure 7b shows network I/O for random and METIS-balanced partitioning when executing different algorithms on the *uk-2007-u* graph, also with 60 workers and 60 compute nodes. The graph plots per superstep network I/O for PageRank and RW-800, and total network I/O for HCC and SSSP. We also experimented with different numbers of workers and compute nodes; we found that network I/O reduction percentages were similar. Of course, network I/O is not the only contributor to overall run-time, so the remainder of our experiments consider the effect of partitioning schemes and other parameters on run-time.

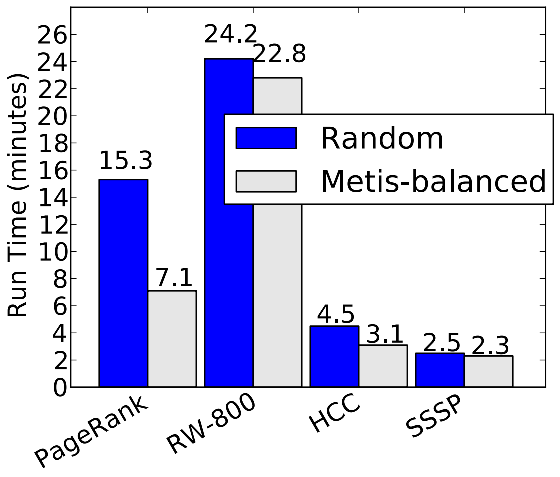
3.2.2 Run-time

In this section, we set out to test how much sophisticated partitioning improves overall run-time. We measure the run-time performance of four algorithms on different graphs, partitioning schemes, and worker and compute node configurations. We used between 15 and 60 nodes, and between one and four workers on each node.

Since the main benefit of sophisticated partitioning is reducing the number of messages



(a) *PageRank (50 iter.) on sk-2005-d*



(b) *Different algorithms on uk-2007-u*

Figure 8: Run-time, different partitioning schemes

sent over the network, we expect partitioning to improve run-time most in algorithms that generate a lot of messages and have low computational workloads. The computation and communication workloads of the graph algorithms we use can be characterized as:

- PageRank: short per-vertex computation, high communication
- HCC: short per-vertex computation, medium communication
- RW-800: long per-vertex computation (due to random number generation), medium communication
- SSSP: short per-vertex computation, low communication

A sample of our experimental results is shown in Figure 8. Figure 8a shows PageRank on the *sk-2005-d* graph on 60 compute nodes with 60 workers. In this experiment, improvements ranged between 1.1x for domain-based partitioning to 2.3x for METIS-balanced. In other experiments for PageRank, METIS-balanced consistently performed best, reducing run-time between 2.1x to 2.5x over random partitioning. Improvements for METIS-default varied from 1.4x to 2.4x and for domain-based partitioning from 1.1x to 1.7x.

Run-time reductions when executing other graph algorithms are less than PageRank, which is not surprising since PageRank has the highest communication to computation ratio of the algorithms we consider. Figure 8b shows four algorithms on the *uk-2007-u* graph using 30 workers running on 30 compute nodes. We compared the performance of random partitioning and METIS-balanced. As shown, METIS-balanced reduces the run-

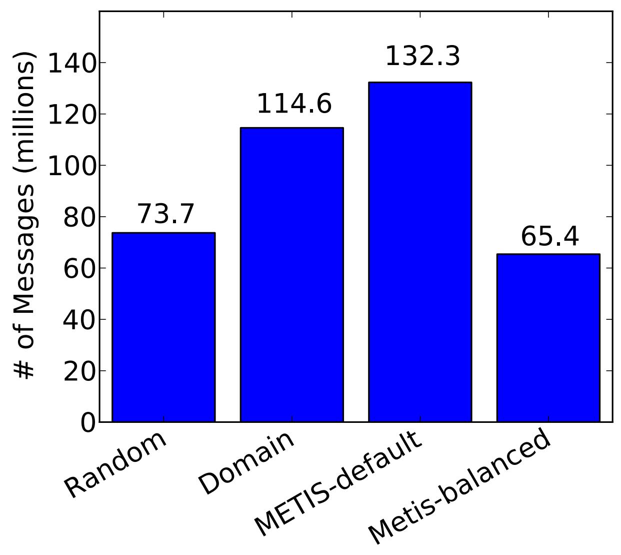


Figure 9: Slowest worker, number of messages.

time by 2.2x when executing PageRank, and by 1.47x, 1.08x, and 1.06x for HCC, SSSP, and RW-800, respectively.

3.2.3 Workload Balance

In all of our experiments reported so far, METIS-default performed better than METIS-balanced in network I/O but worse in run-time. The reason for this counterintuitive performance is that METIS-default tends to create bottleneck workers that slow down the system. For all of the graph algorithms we are considering, messages are sent along the edges. Recall that METIS-default balances only the number of vertices in each partition and not the edges. As a result, some workers process a significantly higher number of messages than average. Figure 9 shows the number of messages processed by the slowest workers in each of the experiments of Figure 8a. The message counts for Random and METIS-balanced indicate fairly homogeneous workloads (perfect distribution would be about 63M messages per worker). But with METIS-default, one partition has more than twice the average load of other partitions, thus slowing down the entire system.

We discuss how to improve workload imbalance, and in turn improve the run-time benefits when using a sophisticated partitioning scheme that can generate imbalanced partitions. One approach is to generate more partitions than we have workers, then assign multiple partitions to each worker, thus averaging the workloads from “heavy” and “light”

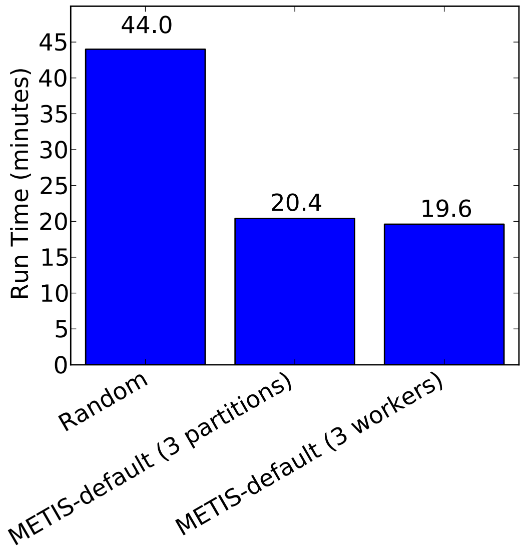


Figure 10: Fixing workload imbalance of METIS-default.

partitions. For example, if we repeat the METIS-default experiment of Figures 8a and 9 but generate 240 partitions and assign each worker four partitions, the slowest worker processes 96M messages instead of the 132M in Figure 9, and run-time is reduced from 9.8 to 8.0 minutes. As a second experiment, we used the original 60 partitions generated by METIS-default, but with only 20 workers on 20 compute nodes, so three partitions assigned to each worker. The result of this experiment is shown in the METIS-default (3 partitions) bar in Figure 10. This set-up improves run-time by 2.2x over random partitioning, significantly better than the 1.4x METIS-default improvement in Figure 8a. We can obtain the same "averaging" effect by assigning one partition to each worker but running multiple workers per compute node. The METIS-default (3 workers) bar in Figure 10 shows the performance of using the 60 partitions generated by METIS-default from before, assigning one partition to each worker, and running three workers per compute node. We see that assigning one partition to each worker and three workers to each compute node performs similarly to assigning three partitions to each worker and one worker to each compute node.

3.3 Experiments on Giraph

The network I/O reductions in our experiments are a direct consequence of the number of edges crossing partitions, determined by the partitioning scheme. Therefore, our network reduction results carry over exactly to other distributed message-passing systems, such as Giraph [GIR]. However, the run-time results are implementation-dependent and may vary

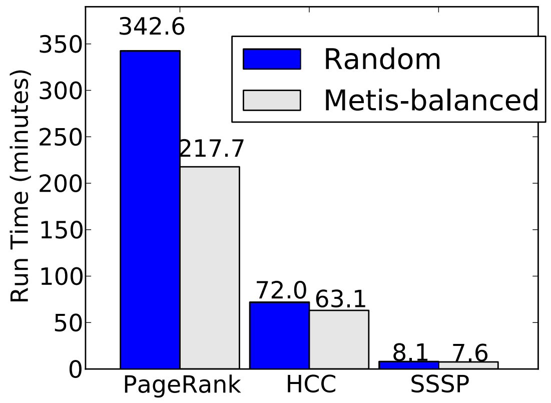


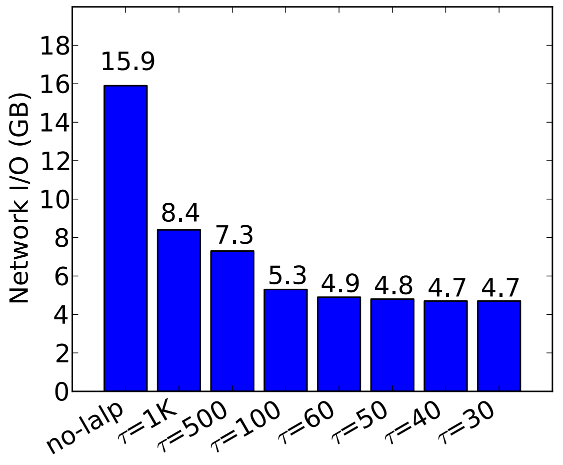
Figure 11: Experiments on Giraph [GIR].

from system to system. To test whether sophisticated partitioning of graphs can improve run-time in other systems, we repeated some of our experiments in Giraph. Figure 11 summarizes our results. METIS-balanced yields 1.6x run-time improvement over random partitioning for PageRank. Similar to our results in GPS, the improvements are less for SSSP and HCC. We also note that GPS runs ∼12x faster than Giraph on the same experiments. We explain the main implementation differences between Giraph and GPS in Section 5.

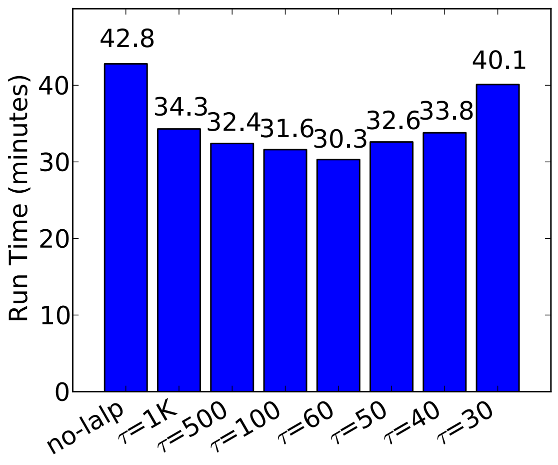
3.4 Large Adjacency-List Partitioning

GPS includes an optimization called *LALP* (large adjacency list partitioning), in which adjacency lists of high-degree vertices are not stored in a single worker, but rather are partitioned across workers. This optimization can improve performance, but only for algorithms with two properties: (1) Vertices use their adjacency lists (outgoing neighbors) only to send messages and not for computation; (2) If a vertex sends a message, it sends the same message to all of its outgoing neighbors. For example, in PageRank each vertex sends its latest PageRank value to all of its neighbors, and that is the only time vertices access their adjacency lists. On the other hand, RW-n does not satisfy property 2: a message from vertex u to its neighbor v contains the number of walkers that move from u to v and is not necessarily the same as the message u sends to its other neighbors.

Suppose a vertex u is located in worker W_i and let $N_j(u)$ be the outgoing neighbors of u located in worker W_j. Suppose $|N_j(u)| = 10000$. During the execution of PageRank, W_i sends 10000 copies of the same message to W_j in each superstep, one for each vertex in $N_j(u)$. Instead, if W_j stores $N_j(u)$, W_i need send only a single message to W_j for node u,



(a) Network I/O



(b) Total run-time

Figure 12: Performance of LALP.

and W_j replicates this message 10000 times to the message queues of each vertex in $N_j(u)$.

Many real-world graphs are known to have a skewed degree distribution, in which a small number of vertices' adjacency lists contain a significant fraction of all the edges in the graph. For these graphs, *LALP* can improve network traffic and run-time significantly. GPS programmers specify a parameter τ when using this optimization. If a vertex u has more than τ outgoing neighbors, GPS partitions *u's* adjacency list into $N_1(u), N_2(u), \ldots, N_k(u)$, and sends $N_j(u)$ to worker W_j during the initial partitioning of the graph across workers. During execution, when u sends a message to all its neighbors, GPS intercepts the message and sends a single a message to each worker W_j, with W_j delivering the message to all vertices in $N_j(u)$.

To verify that LALP improves performance, we ran PageRank on the *twitter-d* graph, with different values of τ, using 32 workers and 16 compute nodes. As we reduce τ, GPS partitions more adjacency lists across all workers, and we expect network I/O to be reduced. On the other hand, as τ is reduced the map of $\langle u, N_j(u)\rangle$ pairs, which each worker W_j maintains, grows, incurring some memory and computation overhead during message parsing. We expect there to be an optimal τ that achieves the best run-time performance. The results of our experiment are shown in Figure 12. Figure 12a shows that decreasing τ decreases network I/O. Figure 12b shows that for our experiment the optimal τ is around 60, and achieves 1.41x run-time improvement over running without LALP.

4 Dynamic Repartitioning

To reduce the number of messages sent over the network, it might be helpful to reassign certain vertices to other workers dynamically during algorithm computation. There are three questions any dynamic repartitioning scheme must answer: (1) which vertices to reassign; (2) how and when to move the reassigned vertices to their new workers; (3) how to locate the reassigned vertices. Below, we explain our answers to these questions in GPS and discuss other possible options. We also present experiments measuring the network I/O and run-time performance of GPS when the graph is initially partitioned by one of our partitioning schemes from Section 3, then dynamically repartitioned during the computation.

4.1 Picking Vertices to Reassign

One option is to reassign vertex u at worker W_i to a new worker W_j if u send/receives more message to/from W_j than to/from any other worker, and that number of messages is over some threshold. There are two issues with this approach. First, in order to observe incoming messages, we need to include the *source* worker in each message, which can increase the memory requirement significantly when the size of the actual messages are small. To avoid this memory requirement, GPS bases reassignment on sent messages only.

Second, using this basic reassignment technique, we observed that over multiple iterations, more and more vertices were reassigned to only a few workers, creating significant imbalance. Despite the network benefits, the "dense" workers significantly slowed down the system. To maintain balance, GPS exchanges vertices between workers. Each worker W_i constructs a set S_{ij} of vertices that potentially will be reassigned to W_j, for each W_j. Similarly W_j constructs a set S_{ji}. Then W_i and W_j communicate the sizes of their sets and exchange exactly $min(S_{ij}, S_{ji})$ vertices, guaranteeing that the number of vertices in each worker does not change through dynamic repartitioning.

4.2 Moving Reassigned Vertices to New Workers

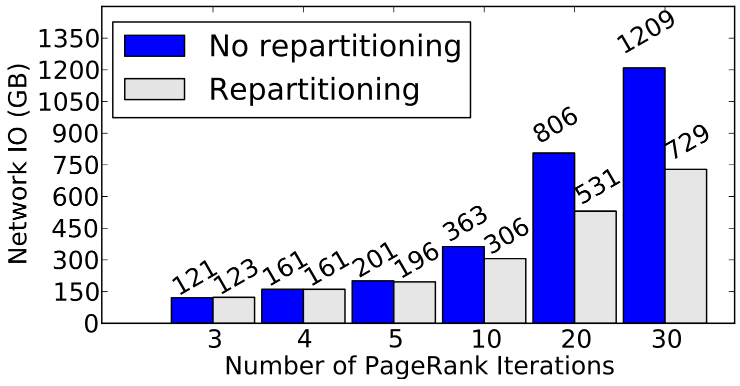
Once a dynamic partitioning scheme decides to reassign a vertex u from W_i to W_j in superstep x, three pieces of data associated with u must be sent to W_j: (a) u's latest value; (b) u's adjacency list; and (c) u's messages for superstep $(x + 1)$. One option is to insert a "vertex moving" stage between the end of superstep x and beginning of superstep $x + 1$, during which all vertex data is moved. GPS uses another option that combines vertex moving within the supersteps themselves: At the end of superstep x, workers exchange their set sizes as described in the previous subsection. Then, between the end of superstep x and beginning of superstep $(x+1)$, the exact vertices to be exchanged are determined and the adjacency lists are relabeled, as described in the next subsection. Relabeling of the adjacency lists ensures that all messages that will be sent to u in superstep $x+1$ are sent to W_j. However, u is not sent to W_j at this point. During the computation of superstep $(x+1)$, W_i first calls *u.compute()* and then sends only u's adjacency list and latest value to W_j. Thus, u's messages for superstep $(x+1)$ are not sent to W_j, reducing the network overhead of dynamic repartitioning.

4.3 Locating Reassigned Vertices

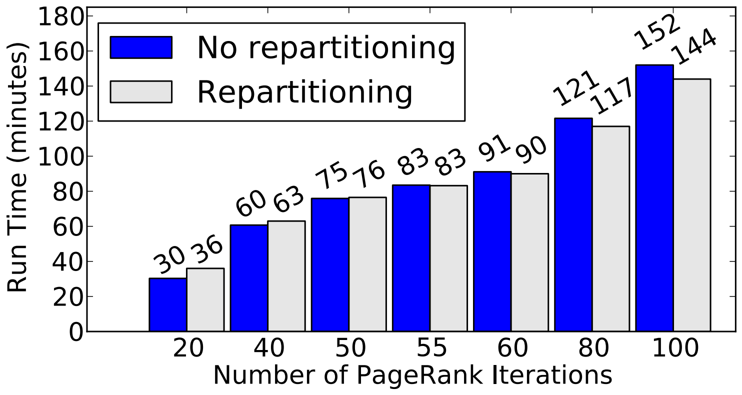
When a vertex u gets reassigned to a new worker, every worker in the cluster must obtain and store this information in order to deliver future messages to u. An obvious option is for each worker to store an in-memory map consisting of <*vertex-id, new-worker-id*> pairs. Of course, over time, this map can potentially contain as many pairs as there are vertices in the original graph, causing a significant memory and computation bottleneck. In our experiments, up to 90% of vertices can eventually get reassigned. Thus, GPS instead uses an approach based on relabeling the IDs of reassigned vertices. Suppose u has been reassigned to W_j. We give u a new ID u', such that $(u' \mod k) = j$. Since every pair W_i and W_j exchange the same number of vertices, vertex IDs can effectively be exchanged as well. In addition, each worker must go through all adjacency lists in its partition and change each occurrence of u to u'.

There are two considerations in this approach:

- If the application requires the original node IDs to be output at the end of the computation, this information must be retained with nodes whose IDs are modified, incurring some additional storage.
- When a node u is relabeled with a new ID, we modify its ID in the adjacency lists of all nodes with an edge to u. If the graph algorithm being executed involves messages not following edges (that is, messages from a node u_1 to a node u_2 where there is no edge from u_1 to u_2), then our relabeling scheme cannot be used. In most graph algorithms suitable for GPS, messages do follow edges.



(a) Network I/O



(b) Run-time

Figure 13: Performance of PageRank with and without dynamic repartitioning.

4.4 Dynamic Repartitioning Experiments

Dynamic repartitioning is intended to improve network I/O and run-time by reducing the number of messages sent over the network. On the other hand, dynamic repartitioning also incurs network I/O overhead by sending vertex data between workers, and run-time overhead deciding which vertices to send and relabeling adjacency lists. It would not be surprising if, in the initial supersteps of an algorithm using dynamic repartitioning, the overhead exceeds the benefits. We expect that there is a crossover superstep s, such that dynamic repartitioning performs better than static partitioning only if the graph algorithm runs for more than s supersteps. Obviously, s could be different for network I/O versus run-time performance, and depends on the graph, graph algorithm, and initial partitioning.

In our first experiment, we ran PageRank on the *uk-2007-d* graph for between 3 and 100 iterations, with random initial partitioning, and with and without dynamic repartitioning.

We used 30 workers running on 30 compute nodes. In GPS, the master task turns dynamic repartitioning off when the number of vertices being exchanged is below a threshold, which is by default 0.1% of the total number of vertices in the graph. In our PageRank experiments, this typically occurred around superstep 15-20. Our results are shown in Figure 13. The crossover superstep in this experiment was five iterations for network I/O and around 55 iterations for run-time. When running PageRank for long enough, dynamic repartitioning gives 2.0x performance improvement for network I/O and 1.13x for run-time.

We repeated our experiment, now initially partitioning the graph using METIS-balanced and domain-based, rather than random. When the initial partitioning is METIS-balanced, we do not see noticeable network I/O or run-time benefits from dynamic repartitioning. On the other hand, when we start with domain-based partitioning, the crossover iteration is 4 for network I/O and 36 for run-time. When running PageRank for long enough, dynamic repartitioning shows 2.2x and 1.2x performance improvement for network I/O and run-time, respectively.

In our setting, the run-time benefits of dynamic repartitioning seem to be modest at best. However, in settings where networking is slower, benefits from network I/O should yield significant run-time improvements as well.

5 Other System Optimizations

We describe several optimizations in GPS that reduce memory usage and increase overall performance.

- **Combining messages at the receiver worker**: *Combiners* were introduced in the MapReduce framework to reduce the number of intermediate values sent from *Mappers* to *Reducers* [DG04], when the Reducers use these values in commutative and associative operations. Similarly, Pregel [MAB$^+$11] uses combiners at the sender and receiver workers to reduce both the number of messages sent between workers and the memory required to store messages in each worker. At the sender sider, when multiple vertices from worker W_i send messages to a vertex v located in W_j, W_i can combine some of these messages at certain intervals and send fewer messages to W_j, reducing network I/O. At the receiver side, when a message m is received in W_j for v, if the message list for v is empty, W_j can add m to v's message list. Otherwise, instead of appending m to the list, W_j can immediately combine its value with the current message in the list. Receiver-side combining reduces the total memory required to store messages for a particular superstep from $|E|$ to $|V|$—a significant reduction in most graphs where the number of edges is significantly higher than the number of vertices.

GPS supports only receiver-side combining. In earlier versions of GPS, we implemented sender-side combining. In order to combine messages at a sender worker W_i, W_i needs to store an outgoing message list for each vertex v that receives a message from W_i, which increases memory usage. Also, messages are buffered twice, once in the outgoing messages lists, and then in the message buffers for each worker, which slows down the rate at which buffers fill and are flushed. Overall, we did not observe significant performance improvements by combining messages at the sender.

- **Single *Vertex* and *Message* objects**: GPS reduces the memory cost of allocating many Java objects by storing *canonical* objects. First, instead of storing the value and the adjacency list of each vertex v inside a separate *Vertex* object, and calling *vertex.compute()* on each object as in Giraph, GPS workers use a single canonical *Vertex* object, with vertex values and adjacency lists stored in separate data structures. For each vertex v in worker W_i, W_i is configured so the canonical *Vertex* object has access to v's value and adjacency list. W_i then calls *vertex.compute()* on the canonical object. Similarly, GPS workers store a single canonical *Message* object. Incoming messages are stored as raw bytes in the message queues, and a message is deserialized into the canonical *Message* object only when the canonical *Vertex* object iterates over it.
- **Controlling the speed of message generation**: Recall from Section 2 that the computation thread generates and buffers outgoing messages by calling *vertex.compute()* on active vertices. When an outgoing message buffer is full, the computation thread gives it to networking threads to send over the network. We have observed that we can significantly improve the overall speed of GPS by controlling the speed of message generation and limiting the number of buffers that are being sent concurrently over the network. GPS controls these factors in two ways. First, at certain intervals, the computation thread checks the number of buffers it has given to the networking layer. If the number is above a threshold (two, by default), the computation thread waits. Second, the networking threads send only a fixed number of the outgoing buffers concurrently over the network (again two, by default). These controls save memory and improve network speed, leading to improved overall performance.

As we showed in Section 3, GPS is ∼12 times faster than Giraph on the graphs and algorithms we tried. In addition to our optimizations above, we believe there are two more implementation differences between GPS and Giraph that explain this differential:

1. **Message Buffers**: Giraph organizes its message buffers per vertex rather than per worker. Both Giraph and GPS wait until buffers are full to send them, or until the end of the superstep when buffers are flushed. Per-vertex buffers take much longer to fill, delaying overall network speed.

2. **Synchronization**: As explained in Section 2, GPS threads synchronize only for each sent and received message buffer. In Giraph, the RPC calls from different workers to a particular worker W_i synchronize with each other, as they access the same message queues in W_i. Therefore, there is possible synchronization between threads for each message received by a worker, which is much more frequent than synchronizing per message buffer.

The system optimizations described in this section have been key to the high performance of GPS; we hope to integrate some of them into Giraph.

6 Related Work

There are several classes of systems designed to do large-scale graph computations:

- **Bulk synchronous message-passing systems**: Pregel [MAB+11] introduced the first bulk synchronous distributed message-passing system, which GPS has drawn from. Several other systems are based on Pregel, including Giraph [GIR], GoldenOrb [GOL], Phoebus [PHO], Hama [HAM], JPregel [JPR] and Bagel [BAG] . Giraph is the most popular and advanced of these systems. Giraph jobs run as Hadoop jobs without the reduce phase. Giraph leverages the task scheduling component of Hadoop clusters by running workers as special mappers, that communicate with each other to deliver messages between vertices and synchronize in between supersteps.
- **Hadoop-based systems**: Many graph algorithms, e.g., computing PageRank or finding connected components, are iterative computations that terminate when a vertex-centric convergence criterion is met. Because MapReduce is a two-phased computational model, these graph algorithms cannot be expressed in Hadoop easily. One approach to solve this limitation has been to build systems on top of Hadoop, in which the programmer can express a graph algorithm as a series of MapReduce jobs, each one corresponding to one iteration of the algorithm. Pegasus [KTF09], HaLoop [BHBE10], iMapReduce [ZGGW11], Surfer [CWHY10] and Twister [ELZ+10] are examples of these systems. These systems suffer from two inefficiencies that do not exist in bulk syn-

chronous message-passing systems: (1) The input graph, which does not change from iteration to iteration, may not stay in RAM, and is sent from mappers to reducers in each iteration. (2) Checking for the convergence criterion may require additional MapReduce jobs.

- **Asynchronous systems**: GPS supports only bulk synchronous graph processing. GraphLab [LGK$^+$10] and Signal-Collect [SBC10] support asynchronous vertex-centric graph processing. An advantage of asynchronous computation over bulk synchronous computation is that fast workers do not have to wait for slow workers. However, programming in the asynchronous model can be harder than synchronous models, as programmers have to reason about the non-deterministic order of vertex-centric function calls. Signal-Collect also supports bulk synchronous processing, but is not a distributed system; its parallelism is due to multithreading.
- **Message Passing Interface (MPI)**: MPI is a standard interface for building a broad range of message passing programs. There are several implementations of MPI [OPE, MPI, PYM, OCA], which can be used to implement parallel message-passing graph algorithms in various programming languages. MPI consists of very low-level communication primitives that do not provide any consistency or fault-tolerance. Programmers must build another level of abstraction (e.g., bulk synchronous consistency) on their own, which makes programming harder than bulk synchronous message-passing systems.
- **Other systems**: HipG [KKFB10] is a system in which each vertex is a Java object and the computation is done sequentially starting from a particular vertex. The code is expressed as if the graph is in a single machine, and the reads and writes to vertices residing in other machines are translated as RPC calls. HipG incurs significant overhead from RPC calls when executing algorithms, such as PageRank, that compute a value for each vertex in the graph. Mahout [MAH] and Spark [ZCF$^+$10] are general cluster computing systems, whose APIs are designed to express generic iterative computations. As a result, programming graph algorithms on Mahout and Spark requires significant more coding effort than on GPS.

In addition to presenting GPS, we studied the effects of different graph partitioning schemes on the performance of GPS when running different graph algorithms. We also studied the effects of GPS's dynamic repartitioning scheme on performance. There are previous studies on the performance effects of different partitionings of graphs on other systems. [HAR11] shows that by partitioning *Resource Description Framework* [RDF04] (RDF) data with METIS and then "intelligently" replicating certain tuples, SPARQL [SPA06] query run-times can be improved significantly over random partitioning. We study the effects of partitioning under batch algorithms, whereas SPARQL queries consist of short path-finding workloads. [SK11] develops a heuristic to partition the graph across machines during the initial loading phase. They study the reduction in the number of edges crossing machines and run-time improvements on Spark when running PageRank. They do not study the effects of other static or dynamic partitioning schemes.

7 Conclusions and Future Work

We presented GPS, an open source distributed message-passing system for large-scale graph computations. Like Pregel [MAB+11] and Giraph [GIR], GPS is designed to be scalable, fault-tolerant, and easy to program through simple user-provided functions. Using GPS, we studied the network and run-time effects of different graph partitioning schemes in a variety of settings. We also described GPS's dynamic repartitioning feature, and presented several other system optimizations that increase the performance of GPS.

As future work, we are interested in exploring which graph algorithms are suitable for running on systems like GPS and Pregel. On the theoretical side, we want to understand exactly which graph algorithms can be implemented efficiently using bulk synchronous processing and message-passing between vertices. For example, although there are bulk synchronous message-passing algorithms to find the weakly connected components of undirected graphs, we do not know of any such algorithm for finding strongly connected components.

On the practical side, we want to offer a higher-level programming interface as an alternative to implementing bulk synchronous message-passing algorithms directly. An analogy would be the Pig [ORS+08] and Hive [TSJ+09] languages implemented on top of Hadoop. As a first step in this direction, we are working on compiling Green-Marl [HCSO12], a domain-specific language for graph algorithms, into GPS.

8 Acknowledgements

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