Supporting On-demand Elasticity in Distributed Graph Processing

Mayank Pundir, Manoj Kumar, Luke M. Leslie, Indranil Gupta, Roy H. Campbell
{pundir2, mkumar11, lmlesli2, indy, rhc}@illinois.edu
University of Illinois at Urbana-Champaign

***Abstract*—While distributed graph processing engines have become popular for processing large graphs, these engines are typically configured with a static set of servers in the cluster. In other words, they lack the flexibility to scale-out/in the number of machines, when requested to do so by the user. In this paper, we propose the first techniques to make distributed graph processing truly elastic. While supporting on-demand scale-out/in operations, we meet three goals: i) Perform scale-out/in without interrupting the graph computation, ii) Minimize the background network overhead involved in the scale-out/in, and iii) Mitigate stragglers by maintaining load balance across servers. We present and analyze two techniques called Contiguous Vertex Repartitioning (CVR) and Ring-based Vertex Repartitioning (RVR) to address these goals. We implemented our techniques in the LFGraph distributed graph processing system, and incorporated several systems optimizations. Experiments performed with multiple graph benchmark applications on a real graph indicate that our techniques perform within 9% of the optimal for scale-out operations, and within 21% for scale-in operations.**

I. Introduction

Large graphs are increasingly common – examples include online social networks like Twitter and Facebook, Web graphs, Internet graphs, biological networks, and many others. As a consequence, distributed graph processing has become attractive in order to perform batch processing of large graphs. Google's Pregel [20] was one of the first such distributed graph processing engines. Subsequently, the research community has developed more efficient engines that adopt Pregel's vertex-centric approach for graph processing, such as LFGraph [11], GraphLab [19], PowerGraph [8], GPS [24], and Hama [2].

Today's graph processing frameworks operate on statically allocated resources; the user must decide resource requirements before an application starts. However, part-way through computation, the user may desire to *scale-out* by adding more machines (e.g., to speed up the computation), or *scale-in* by lowering the number of machines (e.g., to reduce hourly costs). The capability to scale-out/in when required by the user is called *on-demand elasticity*. Such a concept has been explored for datacenters [6] [30], cloud systems [13] [21] [25], storage systems [4] [5] [22] [27] [28] and data processing frameworks such as Hadoop [9] [10] and Storm [3]. However, on-demand elasticity remains relatively unexplored in batch distributed graph processing systems.

While partitioning techniques have been proposed [8] to optimize computation and communication, these techniques partition the entire graph across servers and are thus applicable only at the start of the graph computation. On-demand elasticity requires an *incremental* approach to (re-) partitioning vertices on-demand. Solving the problem of on-demand elasticity is also the first step towards adaptive elasticity (e.g., satisfying an SLA in a graph computation), which can use our techniques as black boxes.

A distributed graph processing system that supports on-demand scale-out/in operations must overcome three challenges:

1) *Perform scale-out/in without interrupting the graph computation.* A scale-out/in operation requires a re-assignment of vertices among servers. For instance, during scale-out, new servers must obtain some vertices (and their values) from existing servers. Similarly, during scale-in, vertices from the departing servers must be re-assigned to the remaining servers.
2) *Minimize the background network overhead involved in the scale-out/in.* To reduce the effect of the vertex transfer on computation time, we wish to minimize the total amount of vertex data transferred during scale-out/in.
3) *Mitigate stragglers by maintaining load balance across servers.* Graph processing proceeds in iterations and stragglers will slow the entire iteration down. Thus, while re-assigning vertices at the scale-out/in point, we aim to achieve load balance in order to mitigate stragglers and keep computation time low.

Our approach to solving the problem of on-demand elasticity and overcoming the above challenges is motivated by two critical questions:

1) **How (and what) to migrate?** Which vertices from which servers should be migrated in order to reduce the network transfer volume and maintain load balance?
2) **When to migrate?** At what points during computation should migration begin and end?

To answer the first question, we present and analyze two new techniques. The first, called *Contiguous Vertex Repartitioning (CVR)*, achieves load balance across servers. However, it may result in high overhead during the scale-out/in operation. Thus, we propose a second technique, called *Ring-based Vertex Repartitioning (RVR)*, that relies on ring-based hashing to lower the overhead. To address the second question (when to migrate) concretely, we integrate our techniques into the

LFGraph graph processing system [11], and use our implementation to carefully decide when to begin and end background migration, and when to migrate static vs. dynamic data. We also use our implementation to explore systems optimizations that make migration more efficient.

We performed experiments with multiple graph benchmark applications on a real Twitter graph with 41.65 M vertices and 1.47 B edges. Our results indicate that our techniques are within 9% of an optimal mechanism for scale-out operations and within 21% for scale-in operations.

II. How (and What) to Migrate?

In this section, we address the question of which vertices to migrate when the user requests a scale-out/in operation.

Most existing distributed graph processing systems use the vertex-centric synchronous Gather-Apply-Scatter (GAS) decomposition, and our techniques are intended for such systems [8] [11] [19] [20] [24]. In vertex-centric graph processing, a vertex (represented by an ID and value) is the basic unit of processing. Graph processing frameworks partition vertices or edges across servers. Computation then proceeds in iterations (sometimes called supersteps). In the synchronous GAS decomposition, each iteration comprises of *gather*, *apply*, and *scatter* stages, wherein each vertex first gathers values from its neighbors, processes and applies the result, and then scatters the updated value to its neighbors. The end of each iteration is synchronized across servers using a barrier server.

Partitioning Assumptions: While some graph processing engines have proposed "intelligent" ways of partitioning vertices across servers before computation starts (e.g., PowerGraph [8]), recent studies have shown that these systems may consume a large fraction of their total run time doing so [11]. For instance, [11] demonstrated that when using PowerGraph to run PageRank on the Twitter graph with 8 servers, 80% of the total runtime was constituted by the intelligent partitioning operation, with subsequent iterations only taking up 20%. The paper [11] concludes that intelligent partitioning techniques are not worth the cost, and shows that hash-based partitioning is simpler and can result in a faster graph computation time.

As a result of these studies, we assume that our base distributed graph processing engine relies on hash-based partitioning. Our contributions and techniques are applicable to all major graph processing engines, including LFGraph [11], Giraph [1], PowerGraph [8] and GPS [24], all of which support hash-based partitioning.

In this remainder of this section, we present two techniques for on-demand elasticity in graph processing. Both techniques assume hash-based partitioning, which works by consistently hashing vertices to a vertex space using a function that assigns m bit values to vertices (e.g., using a hash function like SHA-1). The resulting hashed vertex space ranges from 0 to $2^m - 1$, where m may be set high to minimize collisions. Our two techniques deal with two different and popular ways in which hash-based partitioning is done in graph processing systems.

A. Contiguous Vertex Repartitioning (CVR)

Our first technique assumes that the hashed vertex space is divided into as many partitions as there are servers, and each server is assigned one partition. Partitions are equi-sized in order to accomplish load-balancing. The top of Figure 1a illustrates an example graph containing 100 vertices, split across 4 servers. The vertex sequence (i.e., V_i) is random but consistent due to our use of consistent hashing, and is split into four equi-sized partitions which are then assigned to servers $S_1 - S_4$ sequentially.

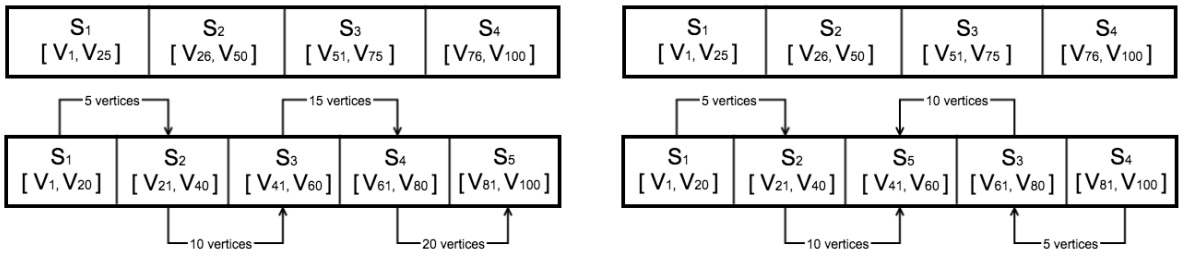
Upon a scale-out/in operation, the key problem we need to solve is: how do we assign the (new) equi-sized partitions to servers (one partition per server), such that network traffic volume is minimized? For instance, the bottom of Figure 1 shows the problem that needs to be solved when scaling out from 4 to 5 servers.To solve this problem, we now: 1) show how to reduce it to a graph matching problem and 2) propose an efficient heuristic.

When we scale-out/in, we repartition the vertex sequence into equi-sized partitions. Assigning these new partitions in an arbitrary fashion to servers may be sub-optimal and transfer large amounts of vertex data across the network. For instance, in the bottom of Figure 1a, we scale-out by adding one server, resulting in five new partitions. Merely adding the new server to the end of the server sequence and assigning partitions to servers in that order results in 50 total vertices being moved. On the other hand, Figure 1b shows the optimal solution for this example, wherein adding the new server in the middle of the partition sequence results in moving only 30 vertices.

To achieve the optimal solution, we consider the scale-out problem formally (the solution for scale-in is similar and not included for brevity). Let the cluster initially have N servers $S_1, \cdots, S_N$. With a graph of V vertices, initially the size of each partition P_i^{old} is $M^{old} = \frac{V}{N}$, where $1 \leq i \leq N$. Each j-th vertex id is first hashed, and the resulting value V_j is initially used to assign it to partition P_i^{old} where $i = \left\lceil \frac{V_j}{M^{old}} \right\rceil$. If we add k servers to this cluster, the size of each new partition becomes $M^{new} = \frac{V}{N+k}$. We label these new partitions as $P_i^{new}, 1 \leq i \leq N+k$, and assign each j-th vertex, as usual, to a new partition by first hashing the vertex id and using the resulting hash V_j to partition P_i^{new} where $i = \left\lceil \frac{V_j}{M^{new}} \right\rceil$.

Next, we create a bipartite graph B, which contains: i) a left set of vertices, with one vertex per new partition P_i^{new}, and ii) a right set of vertices, with one vertex per server S_j. Each of the left and right sets contains $(N+k)$ vertices. The result is a complete bipartite graph, with the edge joining a partition P_i^{new} and server S_j associated with a cost equal to the number of vertices that must be transferred over the network if partition P_i^{new} is assigned to server S_j after scale-out: $|P_j^{old} \cap P_i^{new}| = |P_j^{old}| + |P_i^{new}| - |P_j^{old} \cup P_i^{new}|$.

The problem of minimizing network transfer volume now reduces to finding a minimum-cost perfect matching in B. This is a well-studied problem, and an optimal solution can be obtained by using the Hungarian algorithm [15]. However, the Hungarian algorithm takes $O(N^3)$ time to run [14], which



(a) Sub-optimal partition assignment with total vertex transfer = 50

(b) Optimal partition assignment with total vertex transfer = 30

Figure 1. Scale-out from 4 (top) to 5 (bottom) servers using Contiguous Vertex Repartitioning (CVR).

may be prohibitive for large clusters. As a result, we propose a greedy algorithm that iterates sequentially through $S_1, \cdots, S_N$.[1] For each server S_j, the algorithm considers the new partitions with which it has a non-zero overlap – due to the contiguity of partitions, there are only $O(1)$ such partitions. Among these partitions, that which has the largest number of overlapping vertices with P_j^{old} is assigned to server S_j. This makes the greedy algorithm run efficiently in $O(N)$. For example, in Figure 1b, to determine the new partition for S_1, we need only consider only two partitions $[V_1, V_{20}]$ and $[V_{21}, V_{40}]$. Next, we need to consider partitions $[V_{21}, V_{40}]$ and $[V_{41}, V_{60}]$ and so on.

Section III-A provides a mathematical analysis of the optimal server ordering that minimizes the network transfer volume.

While the technique discussed in this section ensures balanced partitions, it may require a large number of partitions to be re-assigned. This affects a large number of servers because they all transfer vertices, which in turn reduces the resources they can utilize in the ongoing iteration of the graph computation, and prolongs completion time. This drawback motivates our next approach.

B. Ring-based Vertex Repartitioning (RVR)

In this technique, we assume an underlying (initial) hash-based partitioning that leverages Chord-style consistent hashing [27]. To maintain load balance, servers are not hashed directly to the ring, but instead as in [17], [23], we assume each server is assigned an equi-sized segment of the ring. Concretely, a server with ID n_i is responsible for the set of vertices hashed in the interval $(n_{i-1}, n_i]$, where n_{i-1} is n_i's predecessor. The example in Figure 2 shows vertices and servers hashed to $[0, 2^9 - 1]$. Since the predecessor of server with ID 127 is 511, it is responsible for vertices hashed in the interval $(511, 127]$.

Under this assumption performing a scale-out/in operation itself is straightforward – a joining server splits a segment with its successor, while a leaving server gives up its segment to its successor. For instance, in a scale-out operation involving one server, the affected server receives its set of vertices from its successor in the ring, i.e., a server n_i takes the set of vertices $(n_{i-1}, n_i]$ from its successor n_{i+1}. For example, in Figure 2, a new server having ID 63 would take the set of vertices $[0, 63]$ from its successor server. Scale-in operations occur symmetrically: a leaving server n_i migrates its vertex set $(n_{i-1}, n_i]$ to its successor n_{i+1} which will now be responsible for the set of vertices in $(n_{i-1}, n_{i+1}]$.

[1] A similar problem was studied in [7], but their approach is not load-balanced.

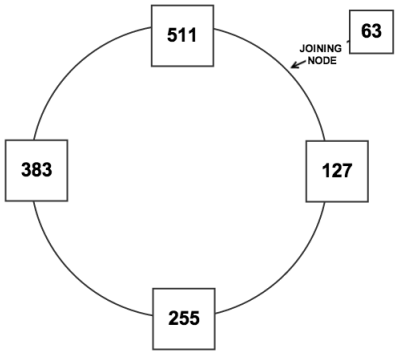


Figure 2. Consistent ring-based hashing of vertices with deterministic server positions with $m = 9$ (2^9 points on the ring).

More generally, we can state that: a scale-out/in operation, which involves k servers being added or removed at once, affects at most k existing servers. If some of the joining or leaving servers have segments that are adjacent, the number of servers affected would be smaller than k.

While this technique is minimally invasive to existing servers and the ongoing graph computation, it may result in load imbalance. We can mitigate load imbalance for the scale-out case by intelligently deciding which point on the ring to add the new server(s). For the scale-in case, we can intelligently decide which server(s) to remove. Due to the mathematical nature of this optimization, we defer this discussion to Section III-B.

III. Mathematical Analysis

In this section, we analyze the two proposed elasticity techniques from Section II. Proofs of our presented theorems can be skipped without loss of continuity.

A. Contiguous Vertex Repartitioning

In this section, we first analyze CVR for scale-out operations, and then for scale-in operations.

1) Scale-out: Assume a computation is running on a graph with V vertices, and suppose the user performs a scale-out operation by adding one server. Consider a case where the order of the old servers is retained, but the new server is inserted at a position k, i.e., right after server S_k^{old} but before S_{k+1}^{old}, $0 \leq k \leq N$ (there, there are $N+1$ potential locations for adding the new server). We wish to identify which insertion position minimizes network traffic volume.

Theorem 1. *Consider a cluster of N servers running a computation on a graph with V vertices. Initially, the system is load balanced (each server has $\frac{V}{N}$ vertices). If we add a new server to the cluster using our CVR approach, without changing the order of the old servers, then the total network transfer volume is minimized if the new server is added immediately after old server $S_{\frac{N}{2}}$, i.e., halfway through the list of old servers.*

Proof. For a given value of k, let $t_{so}(i)$ be the number of vertices migrated *from* the server at old position i ($1 \leq i \leq N$). The servers at positions to the left of the new server (i.e., $i < k$) will transfer some vertices to their immediate right neighbors, while the servers to the right of this position (i.e., $i \geq k$) transfer vertices to their left neighbors (see Figure 1 for an illustration). Initially, each server holds $\frac{V}{N}$ vertices; after scale-out, each server would hold $\frac{V}{N+1}$ vertices. Hence, each server contributes $(\frac{V}{N} - \frac{V}{N+1})$ vertices to its neighbor, and these are accumulated across all old partitions to populate the new server's partition with $(\frac{V}{N} - \frac{V}{N+1}) \times N = \frac{V}{N+1}$ vertices. Servers which receive vertices from a neighbor pass on as many vertices to their next neighbor, giving us:

$$\begin{aligned} t_{so}(i=1) &= \frac{V}{N} - \frac{V}{N+1} && if\ 0 < k \leq N \\ t_{so}(i=N) &= \frac{V}{N} - \frac{V}{N+1} && if\ 0 \leq k < N \\ t_{so}(i) &= t_{so}(i-1) + \frac{V}{N} - \frac{V}{N+1} && for\ 1 < i \leq k \\ t_{so}(i) &= t_{so}(i+1) + \frac{V}{N} - \frac{V}{N+1} && for\ k < i < N \end{aligned} \tag{1}$$

This can be solved to give:

$$\begin{aligned} t_{so}(i) &= i \times \left(\frac{V}{N \times (N+1)}\right) && for\ 1 \leq i \leq k \\ t_{so}(i) &= (N-i+1) \times \left(\frac{V}{N \times (N+1)}\right) && for\ k < i \leq N \end{aligned} \tag{2}$$

The total number of vertices migrated by all servers put together is therefore:

$$\begin{aligned} C_{so}(k) &= \sum_{i=1}^{N} t_{so}(i) \\ &= \frac{V}{N \times (N+1)} \times \left(\sum_{i=1}^{i \leq k} i + \sum_{i=k+1}^{i \leq N} (N-i+1)\right) \\ &= \frac{V}{N \times (N+1)} \times \left(\frac{2 \times k^2 + N^2 + N - 2 \times k \times N}{2}\right) \end{aligned} \tag{3}$$

By solving for $\frac{d}{dk} C_{so}(k) = 0$ (and checking that the second derivative is positive), we find that $C_{so}(k)$ is minimized when $k = k^* = \frac{N}{2}$. The minimal number of vertices transferred is therefore $C_{so}^* = \frac{V \times (N+2)}{4 \times (N+1)}$ and we have the following theorems. □

2) Scale-in: Assume a computation running on a graph with V vertices and suppose the user performs a scale-in operation by removing one server. We assume the user only specifies the number of servers to remove, and we have flexibility in selecting *which* server to remove – this is a reasonable assumption, for instance, in graph computations running on virtualized platforms. (If the user specifies the particular server to remove, the problem is not challenging.)

We consider a case where the order of the old servers is retained but the leaving server is removed from position k, i.e., right after server S_{k-1}^{old} but before S_{k+1}^{old} ($1 \leq k \leq N$). This gives us N total choices for removing the leaving server. We now analyze which of these positions minimizes network traffic volume using a similar approach as scale-out.

Theorem 2. *Consider a cluster of N servers running a computation on a graph with V vertices. Initially, the system is load balanced (each server has $\frac{V}{N}$ vertices). If we remove one server from the cluster using our CVR approach, then the total network transfer volume is minimized if the leaving server is removed immediately after old server $S_{\frac{N+1}{2}}$, i.e., halfway through the list of old servers. The minimal number of vertices transferred in this case is $C_{si}^* = \frac{V \times (N+1)}{4 \times N}$.*

Proof. For a given value of k, let $t_{si}(i)$ be the number of vertices migrated *from* the server at old position i ($1 \leq i \leq N$). The leaving server transfers $\frac{V(k-1)}{N(N-1)}$ vertices to its left neighbor while $\frac{V(N-k)}{N(N-1)}$ vertices to its right neighbor. This is because it proportionally transfers its vertex set to the servers on its left and right side. The servers at positions to the left of the leaving server (i.e., $i < k$) will transfer some vertices to their immediate left neighbors, while the servers to the right of this position (i.e., $i > k$) transfer vertices to their right neighbors. Initially, each server holds $\frac{V}{N}$ vertices. After scale-in, each server would hold $\frac{V}{N-1}$ vertices. This reasoning gives us:

$$\begin{aligned} t_{si}(i=1) &= 0 && if\ 1 < k \leq N \\ t_{si}(i=N) &= 0 && if\ 1 \leq k < N \\ t_{si}(i) &= t_{si}(i+1) + \frac{V}{N} - \frac{V}{N-1} && for\ 1 < i < k \\ t_{si}(i) &= t_{si}(i-1) + \frac{V}{N} - \frac{V}{N-1} && for\ k < i < N \end{aligned} \tag{4}$$

This can be solved to give:

$$\begin{aligned} t_{si}(i) &= (k-i)\left(\frac{-V}{N \times (N-1)}\right) + \frac{V \times (k-1)}{N \times (N-1)} && for\ 1 \leq i \leq k \\ t_{si}(i) &= (i-k)\left(\frac{-V}{N \times (N-1)}\right) + \frac{V \times (N-k)}{N \times (N-1)} && for\ k \leq i \leq N \end{aligned} \tag{5}$$

Now, the *total* number of vertices migrated by all servers put together is:

$$\begin{aligned} C_{si}(k) &= \sum_{i=1}^{N} t_{si}(i) \\ &= \frac{-V}{N\times(N-1)}\left(\sum_{i=1}^{i\le k}(k-i)+\sum_{i=k}^{i\le N}(i-k)\right) \\ &+ (k-1)\frac{V\times(k-1)}{N\times(N-1)} + (N-k)\frac{V\times(N-k)}{N\times(N-1)} + \frac{V}{N} \\ &= \frac{V}{N\times(N-1)}\left(\frac{N^2+2k^2-2Nk-2k-N+2}{2}\right)+\frac{V}{N} \end{aligned} \tag{6}$$

By solving for $\frac{d}{dk}C_{si}(k)=0$ (and checking the second derivative is positive) we find that $C_{si}(k)$ is minimized when $k=k^*=\frac{N+1}{2}$. The minimal number of vertices transferred is $C^*_{si}=\frac{V\times(N+1)}{4\times N}$. □

B. Ring-based Vertex Repartitioning

In this section, we first analyze our RVR technique for scale-out/in operations with one server, and then with multiple servers.

1) One Server: We can state the following theorems for our RVR technique:

Theorem 3. *For a scale-out operation involving adding one server to a balanced cluster, the minimal number of vertices transferred by our RVR technique is* $\frac{V}{2N}$.

Theorem 4. *For a scale-in operation involving removing one server from a balanced cluster, the number of vertices transferred by our RVR technique is* $\frac{V}{N}$.

In the former theorem, this minima occurs when the new server is added half-way between two existing (old) servers.

2) Multiple Servers: Once again, like in Section III-A2 we assume that we are given the number of servers to remove, but we have flexibility in selecting which servers to remove. When scaling-out/in with multiple servers, more than one partition may be affected. In both cases, our approach is to "spread out" the affected portions over the ring over disjoint segments – this preserves load balance the most. For instance, in scale-out if we add servers to disjoint old partitions in the ring, then as long as the cluster adds fewer than $(N+1)$ additional servers, the result of Theorem 3 holds. Similarly for scale-in as long as fewer than $(\frac{N}{2}+1)$ servers are removed, alternating servers can be removed and the result of Theorem 4 holds.

However, this strategy does not work when scaling out with more than N servers or scaling in with more than $N/2$ servers. In this case, we can more generally state:

Theorem 5. *Consider a cluster with N servers running a graph computation; initially, each server has $\frac{V}{N}$ vertices. Consider a scale-out operation which adds $k>N$ servers to the cluster using RVR. Some subgroups of these new servers will be added to the same old partition (we assume they are equally distributed inside the old partition). Let m be the maximum size of such a group, i.e., the maximum number of new servers added to an old partition. Then, the approach of spreading out is minimax (i.e., minimizes the maximum loaded server) if $(m-1)\times N < k \le m\times N$.*

Proof. The proof follows from our strategy of assigning the first N new servers each to a disjoint old partition, then in the second round iterating through the next N servers and assigning them again to the N old partitions, and so on for a total number of $\lceil\frac{k}{N}\rceil$ rounds. Since new servers are evenly distributed inside an old partition, this achieves the minimax. □

Similarly, we can state and prove the above theorem for the scale-in case.

Theorem 6. *Consider a cluster with N servers running a graph computation; initially each server has $\frac{V}{N}$ vertices. Consider a scale-in operation which removes $k>N/2$ servers from the cluster using RVR. Some subgroups of these servers will be removed contiguously from the ring. Let m be the maximum size of such a group, i.e., the maximum number of servers removed from an old partition. Then, the approach of spreading out is minimax (i.e., minimizes the maximum loaded server) if $\frac{(m-1)\times N}{m} < k \le \frac{m\times N}{m+1}$.*

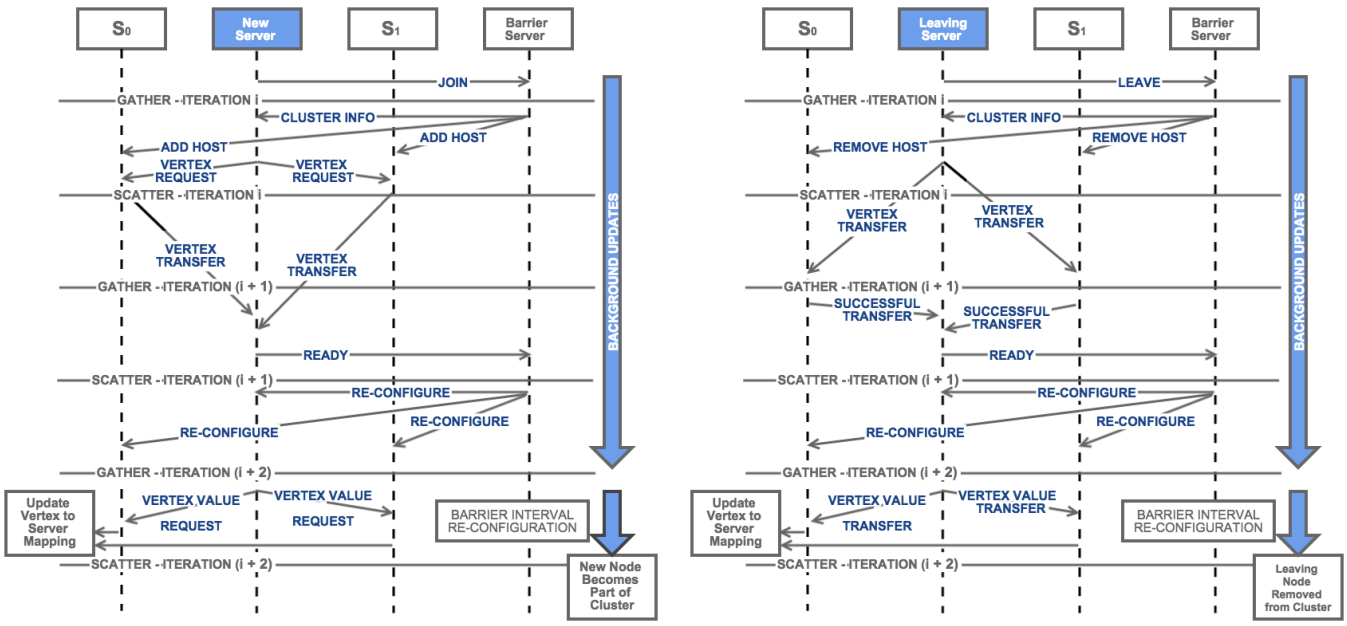
Proof. The proof follows from our strategy of first removing $\frac{N}{2}$ servers so that no two successors are removed, then removing (in the second round) the next $\frac{N}{4}$ servers so that no two successors are removed, and so on for a total number of $\lceil -log_2(1-\frac{k}{N})\rceil$ rounds (the number of rounds can be derived from the geometric progression sum). Since leaving servers are evenly distributed across the partitions of remnant (non-leaving) servers, this achieves the minimax. □

C. Similarities

While CVR and RVR are different ways of hash-based partitioning, there are some corner cases where our techniques output the same new assignment of vertices to servers. One of them is shown below.

Theorem 7. *Consider a cluster with N servers each having $\frac{V}{N}$ vertices. If we add $m\times N$ servers or remove $\frac{m\times N}{m+1}$ servers (for $m\ge 1$) using CVR, then the optimal position of servers to be added or removed is same as their position with RVR.*

Proof. A scale-out technique achieves the minimum total network transfer volume (number of vertices migrated) if the extra vertices at existing servers due to scale-out are directly migrated to the new servers. Similarly, a scale-in technique achieves the minimum total network transfer volume if the vertices from leaving servers are directly migrated to the server that will finally be responsible for them. If we add $m\times N$ servers or remove $\frac{m\times N}{m+1}$ servers, we can achieve this by adding m servers to each of the N existing partitions or removing m servers from each of the $\frac{N}{m+1}$ remnant partitions. That is, the optimal position of servers to be added or removed with RVR is same as their position with CVR. □



(a) Scale-out procedure

(b) Scale-in procedure

Figure 3. Stages in scale-out and scale-in operations.

IV. When to Migrate?

Given the knowledge of which vertices must be migrated and to where, we must now decide *when* to migrate them in such a way that minimizes interference with normal execution. Two types of data need to be migrated between servers: (i) static data, including sets of vertex IDs, neighboring vertex IDs and edge values to neighbors, and (ii) dynamic data, including the latest values of vertices and latest values of neighbors. Static data corresponds to graph partitions, while dynamic data represents computation state. Once this migration is completed, the cluster can switch to the new partition assignment.

A. LFGraph Overview

We have incorporated our elasticity techniques into LFGraph [11], a vertex-centric graph processing framework. We have chosen LFGraph because it offers low computation and communication load, low pre-processing cost and low memory consumption. However, our proposed techniques are not limited to LFGraph and can be incorporated into any synchronous framework configured to use random partitioning or hash-based partitioning, such as Giraph [1], PowerGraph [8], and GPS [24].

LFGraph uses hash-based partitioning of vertices across servers for efficient pre-processing. Each server's partition is further divided into equi-sized vertex groups so that each group can be assigned to a separate worker thread. Gather and scatter phases across servers are independent of each other but are synchronized across servers at the end of each iteration using a barrier server.

B. Executing Migration

LFGraph uses a publish-subscribe mechanism. Before the iterations start, each server subscribes to in-neighbors of the vertices hosted by the server. Based on these subscriptions, servers build a publish list for every other server in the cluster. After each iteration, servers send updated values of the vertices present in the publish lists to the respective servers. After a scale-out/in operation, we perform the publish-subscribe phase again to update the publish lists of servers.

1) First-cut Migration: A first-cut approach is to perform migration of both static and dynamic data during the next available barrier synchronization interval. However, when we implemented this approach, we found that it added significant overheads by prolonging that iteration. As a result, we introduce our next two optimizations.

2) Static Data Migration: This technique is based on the observation that static data can be migrated in the background while computation is going on. Recall that static data consists of vertex IDs, their neighboring vertex IDs and edge values to neighbors. Only dynamic data (vertex values and neighboring vertex values) needs to wait to be migrated during a barrier synchronization interval (i.e., after such data is last updated). This reduces the overhead on that iteration.

3) **Dynamic Data Migration:** LFGraph has two barrier synchronization intervals. One interval is between the gather and scatter phases and the other is after the scatter phase. This gives us two options for the transfer of dynamic data. We perform dynamic data transfer and cluster re-configuration in the barrier synchronization interval *between* the gather and scatter phases. This enables us to leverage the default scatter phase to migrate neighboring vertex values. The scatter phase simply considers the new set of servers in the cluster while

distributing updated vertex values. This optimization further reduces the overhead on that iteration.

Figure 3 shows the above optimizations in practice and the barrier server's role in synchronizing scale-out/in operations. We give an overview first. A scale-out/in operation that starts in iteration i ends in iteration $i+2$. Background static data migration occurs in iterations i and $i+1$ while vertex value migration occurs after the gather phase of iteration $i+2$. At this point, the cluster is re-configured and computation continues on the new set of servers. The performance impact due to background data migration is more in iteration i than in iteration $i+1$, i.e., iteration times are longer in iteration i. This is because a majority of the migration happens in iteration i. In iteration $i+1$, servers build their new subscription lists for the publish-subscribe phase.

In more detail, Figure 3a shows the following steps involved in a scale-out: (1) The joining server sends a *Join* message containing its IP address and port to the barrier server at the start of iteration i. (2) The barrier server responds with a *Cluster Info* message assigning the joining server an ID and the contact information of the servers from which it should request its vertices. (3) Additionally, the barrier server sends an *Add Host* message to all servers informing them about the new server in the cluster. (4) The joining server requests its vertices with a *Vertex Request* message. (5) After receiving its vertices, it informs the barrier server that it can join the cluster with a *Ready* message. Concurrently, the servers start updating their subscription lists to reflect the modifications in the cluster servers (this is our Background subscription lists optimization discussed in Section V). (6) The barrier server sends a *Re-configure* message to the servers in the synchronization interval after gather phase of iteration $i+2$. (7) Upon receiving the *Re-configure* message, joining servers request the vertex values with a *Vertex Value Request* message. Additionally, all servers update their vertex-to-server mapping to reflect newly added servers. (8) The scatter phase of iteration $i+2$ executes with this new mapping on the new set of servers in the cluster. From this point on, computation proceeds on the new set of servers.

Similarly, Figure 3b shows the timeline for a scale-in operation. (1) The leaving server sends a *Leave* message to the barrier server at the start of iteration i. (2) The barrier server responds with a *Cluster Info* message giving the leaving server the contact information of the servers to which it should transfer its vertices. (3) Additionally, the barrier server sends a *Remove Host* message to all the servers in the cluster informing them about the server leaving the cluster. (4) The leaving server starts transferring its vertices to the servers that will be responsible for them with a *Vertex Transfer* message. (5) The remnant (non-leaving) servers send a *Successful Transfer* message to the leaving server after receiving the vertices. (6) The leaving server, upon receiving these messages, informs the barrier server that it can leave the cluster with a *Ready* message. Concurrently, the remnant servers start updating their subscription lists to reflect the modifications in the cluster servers.(7) The barrier server sends a *Re-configure* message to the servers in the synchronization interval after gather phase of iteration $(i+2)$. (8) Upon receiving the *Re-configure* message, the leaving server transfers the vertex values to the servers that received its set of vertices with *Vertex Value Transfer* messages. Additionally, all servers update their vertex-to-server mapping to reflect newly added servers. (9) The scatter phase of iteration $i+2$ executes with this new mapping on the new set of servers in the cluster. From this point on, computation proceeds on the new set of servers.

4) Role of Barrier Server: In our repartitioning techniques, the barrier server accepts server-join and server-leave requests and determines an optimal partition assignment. We adopted this approach instead of a fully decentralized re-assignment because of two reasons: i) fully decentralized re-assignment may lead to complex race conditions, and ii) the barrier server, being initialized, has the capability to obtain per-server iteration run times via the barrier synchronization messages and could assign new servers to alleviate the load on the busiest servers.

V. Optimizing Migration

In this section, we discuss specific performance optimizations available for migration in frameworks such as LFGraph.

A. Parallel Migration

LFGraph uses consistent hashing to split the vertices assigned to a server (a partition) further into *vertex groups*, with each vertex group assigned to a separate thread [11]. If two servers are running the same number of threads, we can use a parallel migration optimization that works as follows. The (consistent hashing) ring inside each server is identical, as are the segments of the ring (each segment corresponding to a vertex group). As a result, there is a one-to-one correspondence between segments (and thus threads) across two servers. On a scale-out/in operation, data can be transferred directly and parallely between these corresponding threads.

B. Efficiency vs. Overhead Trade-off

Speeding up the background migration via parallelism slows the ongoing computation. On the other hand, if migration is performed serially, the time taken for transferring vertex data would increase. To achieve a balance between the two, we propose two further optimizations:

- *Thread-Count*: We use half as many threads as vertex groups. The result is a conservative use of the network resource, at the expense of slower background migration.
- *Background Subscription Lists*: We allow nodes to start receiving information in the background (from the barrier server) about joining or leaving servers (*Add Host* messages in Figure 3). This allows them to start building subscription lists before the actual cluster re-configuration phase. Although this can be performed in parallel for each vertex group, we perform it serially to reduce the impact on ongoing computation.

C. Ring-based Optimizations

For scale-in operations using RVR, two further optimizations are possible:

- *Modified Scatter*: We perform a modified scatter phase after vertex transfer (in iteration $i+2$ in Figure 3) where servers transfer vertex values, subscribed by leaving servers, to their respective successors. Additionally, we leverage this scatter phase to have a leaving server transfer all vertex values to its successor while only subscribed values are sent to other servers. This optimization allows the scatter phase to be performed in parallel with cluster re-configuration after scale-out/in operation. Additionally, it avoids using an explicit vertex value migration step during the barrier interval as leaving servers migrate the vertex values as part of the modified scatter phase.
- *Subscription Lists*: For a scale-in, we quickly rebuild subscription lists at each remnant (non-leaving) server by merely appending the subscription list for a leaving server S to S's next remnant successor – in RVR, S's successor inherits leaving server S's vertices. This avoids rebuilding subscription lists from scratch at remnant servers.

VI. Evaluation

In this section, we experimentally evaluate the efficiency and overhead of our elasticity techniques.

A. Experimental Setup

We perform our experiments with both our CVR and RVR techniques on virtual instances each having 16 GB RAM and 8 VCPUs. We use the Twitter graph which is publicly available [16] and contains 41.65 M vertices and 1.47 B edges (with larger graphs, we expect similar performance improvements). We evaluate our techniques using five graph benchmarks: PageRank, single-source shortest paths (SSSP), connected components, k-means clustering and multiple-source shortest paths (MSSP).

B. Scale-out and Scale-in

Our first set of experiments measures the overhead experienced by the computation due to a scale-out operation. Figure 4 shows two experiments that perform a scale-out from X servers to $2X$ servers (for $X \in \{5, 10, 15\}$), with the scale-out starting at iteration $i = 1$ and ending at iteration 3. The vertical axis plots the *per-iteration* run time. For comparison, we plot the per-iteration times for a run with X servers throughout, and a run with $2X$ servers throughout.

From Figures 4a and 4c, we observe that: i) both CVR and RVR appear to perform similarly, and ii) after the scale-out operation is completed, the performance of the scaled-out system converges to that of a cluster with $2X$ servers, demonstrating that our approaches converge to the desired throughput after scale-out.

Similarly, Figure 5 shows the plots for scale-in from $2X$ servers to X servers (for $X \in \{5, 10, 15\}$). Once again, the cluster converges to the performance of X servers. However, RVR has a lower overhead than CVR – this is due to the Ring-based optimizations discussed for scale-in in Section V-C.

C. How Close are we to Optimal?

Figures 4 and 5 showed that iterations take longer during scale-out/in. If the vertex migration had infinite bandwidth available for it, then the scale-out/in could be done *instantly* at the end of some iteration. We call this the *Ideal Technique*. The ideal technique is in fact the best possible (i.e., optimal) performance one can get when scaling out/in. Figure 6 shows the overhead of our technique compared to this ideal technique. The overhead captures the extra time spent by our technique in running the entire graph computation during one scale-out/in operation occurring from iteration $i = 1$ to $i = 3$. The overhead is computed as follows. First we assume the ideal technique instantly scales-out/in after iteration $i = 3$ – thus we plot its timeline (similar to Figures 4, 5) as the timeline for X servers up to the third iteration and as the timeline for $2X$ servers beyond the third iteration. We calculate the overhead as the area of the plot between our technique's line and the ideal line below it.

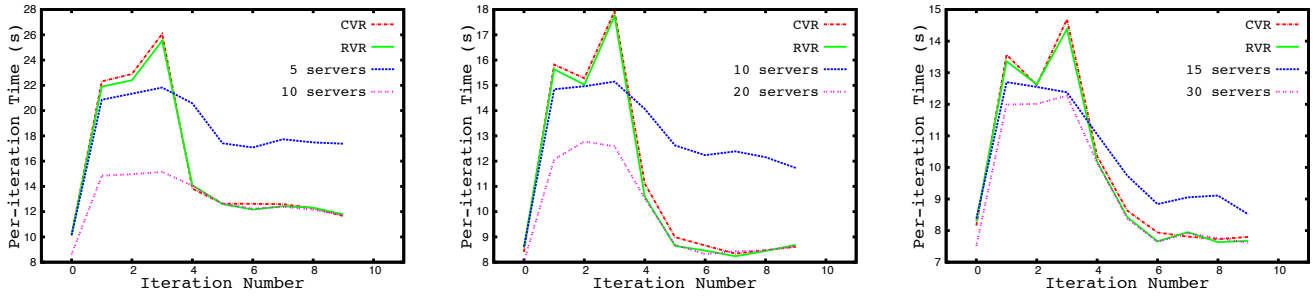
Figure 6 shows that for PageRank our techniques result in less than 5% total overhead for scale-out compared to the ideal technique. For scale-in operations, RVR incurs less than 8% total overhead while CVR incurs less than 11% total overhead. Further, with increasing cluster size, the percentage overhead falls for both scale-out and scale-in – this is because lesser data needs to be migrated per server as the cluster size increases.

For short computations with one scale-out/in operation, affecting fewer servers, as achieved by RVR, is more important than achieving an optimal assignment of vertices to servers. However, the caveat is that if the graph computation were a very long-running one, and involved multiple scale-out/in operations during its lifetime, then RVR would result in stragglers and prolong the computation.

a) Scale-out vs. Scale-in Overhead: : We observe that the overhead numbers in Figure 6 (and later plots) for scale-in are higher than that of scale-out. This is purely an artifact of the way we constructed the ideal technique. Comparing Figures 4a and 5a for instance, we notice that during the scaling (iterations $i = 1$ to 3), the absolute overhead for scale-out and scale-in are comparable (CVR line and RVR line both peak at about 26 s iteration time). However, for scale-in, the ideal technique's curve is much lower than it is for scale-out (during iterations $i = 1$ to 3), because the former used a large number of servers prior to the scaling and thus the per-iteration time was lower. This results in the overhead (area between our technique's line and the ideal technique's line during iterations $i = 1$ to 3) being measured as higher for scale-in than for scale-out.

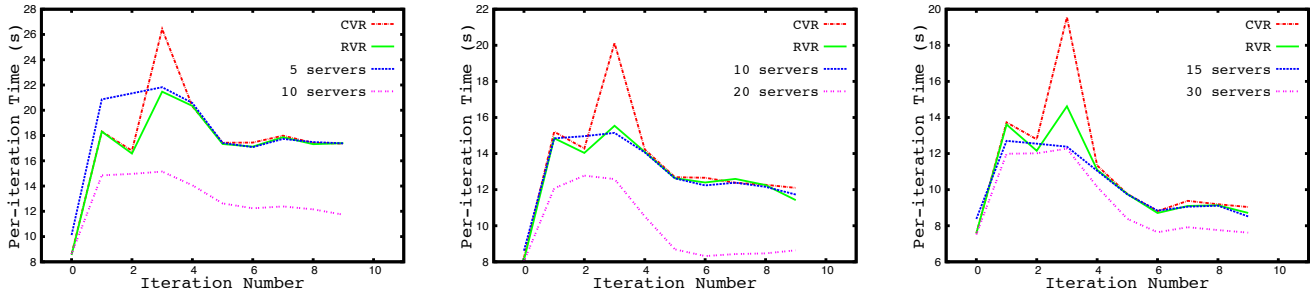
D. Scale-out and Scale-in at Various Points in Computation

We evaluate the effect of starting the scale-out/in operation at different iterations in computation. Figure 7 shows this overhead with 5 to 10 servers scale-out and 10 to 5 servers scale-in performed at iterations $i \in \{1, 2, 3, 4, 5, 6\}$ with PageRank algorithm. The plot shows that our techniques incur less than 6% overhead during scale-out and less than 11% overhead during scale-in, compared to the ideal technique. The absolute



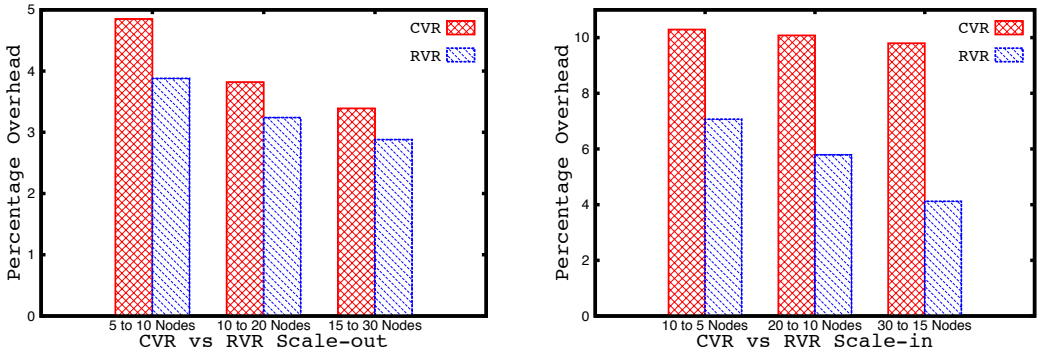
(a) Scale-out from 5 to 10 servers (b) Scale-out from 10 to 20 servers (c) Scale-out from 15 to 30 servers

Figure 4. Per-iteration execution time with scale-out at iterations $i = 1$ to $i = 3$.



(a) Scale-in from 10 to 5 servers (b) Scale-in from 20 to 10 servers (c) Scale-in from 30 to 15 servers

Figure 5. Per-iteration execution time with scale-in at iterations $i = 1$ to $i = 3$.



(a) Scale-out (b) Scale-in

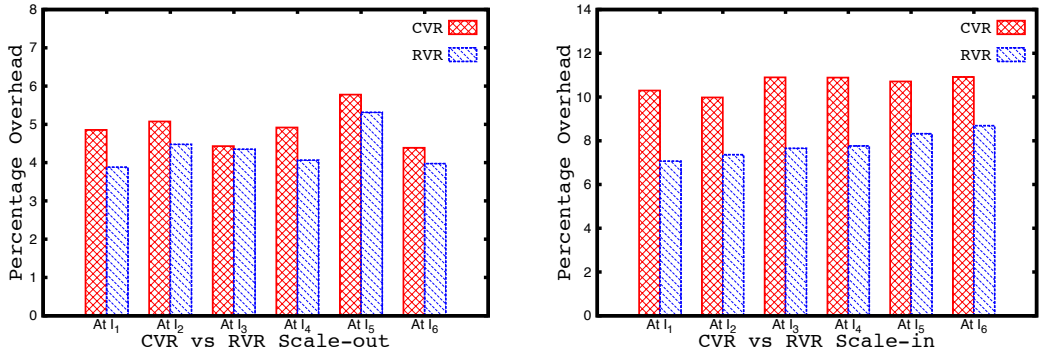
Figure 6. PageRank overhead comparison with the Ideal Technique with 5 to 10 servers scale-out and 10 to 5 servers scale-in.

overhead does not depend on the iteration number. However, the total execution time of the ideal technique is larger if the scale-out is performed in later iterations and smaller if the scale-in is performed in later iterations. This is because of shorter later iterations of PageRank. This causes, for example, the percentage overhead to increase if the scale-in is performed in later iterations, as observed in Figure 7b.

E. Scale-out and Scale-in for Various Algorithms

Figure 8 shows the overhead incurred with the four other graph benchmarks: SSSP, k-means clustering, connected components and MSSP. For k-means clustering, we chose 100 as the number of clusters. Even though k-means clustering spans multiple sets of iterations with different sets of clusters, we calculate overhead only in the set of iterations where the scale-out/in operation is performed. For MSSP, we computed the shortest paths to 10 landmark vertices in the graph.

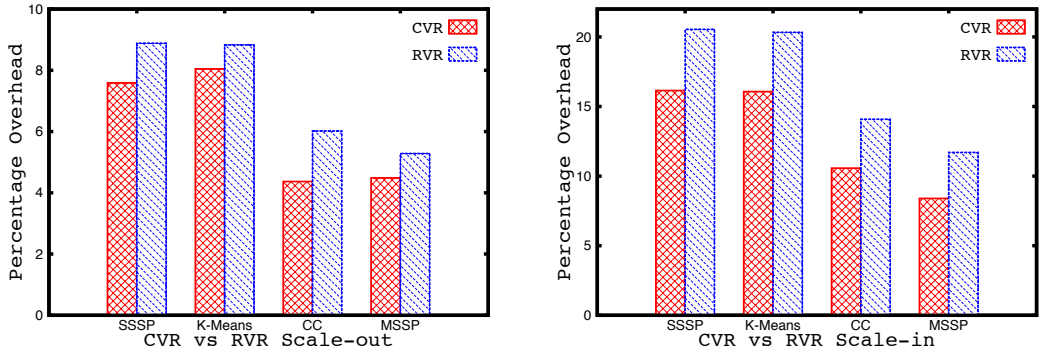
The plots show that across algorithms, we incur less than 9% overhead for scale-out, and less than 21% overhead for scale-in, all compared to the ideal technique (the difference between the numbers was explained in Section VI-C). The overheads for SSSP and k-means clustering algorithms are higher than others because of a smaller total execution time. The total



(a) Scale-out

(b) Scale-in

Figure 7. PageRank overhead comparison with the Ideal Technique with 5 to 10 servers scale-out and 10 to 5 servers scale-in at different iteration times where I_i represents iteration i.



(a) Algorithms overhead comparison in scale-out

(b) Algorithms overhead comparison in scale-in

Figure 8. Overhead comparison with the Ideal Technique with 5 to 10 servers scale-out and 10 to 5 servers scale-in in single-source shortest paths (SSSP), k-means clustering, connected components (CC), and multiple-source shortest paths (MSSP).

Table I
HUNGARIAN VS. GREEDY TIME COMPARISON FOR PARTITION ASSIGNMENT IN THE CASE OF DOUBLING THE NUMBER OF SERVERS.

Servers	Hungarian Time (ms)	Greedy Time (ms)
50	0.053	0.010
100	0.166	0.011
200	0.641	0.019
300	1.114	0.047
400	3.931	0.087
500	16.095	0.151
1000	183.595	0.224
2000	632.161	0.508

execution time for SSSP and k-means clustering algorithms is within 80-90 s, while the total execution time is within 150-160 s for PageRank, within 120-130 s for connected components and within 190-200 s for MSSP. Although total execution time for MSSP is more than PageRank, MSSP incurs a higher overhead. This is because in MSSP, the vertex value set is much bigger – each vertex stores a set of 10 values representing shortest distance from 10 randomly chosen landmarks to the vertex.

Scale-out/in operations took 2 iterations to complete for connected components but took 3 iterations for SSSP, k-means clustering and MSSP. The additional iteration was needed because these algorithms have short initial iterations.

F. Performance of Greedy Algorithm for Partition Assignment

Finally, we present a comparison between the greedy algorithm described in Section II-A and the classical Hungarian algorithm. We present results from a simulation experiment using a publicly available C implementation [12] for the Hungarian algorithm and our C implementation for our greedy algorithm. Table I shows the time taken to calculate the partition assignment when doubling the cluster size. In all cases, our greedy algorithm finds the partition assignment much quicker than Hungarian. As our experiments have shown, the resulting overhead (due to greedy) are low.

VII. RELATED WORK

To the best of our knowledge, we are the first to explore elasticity for distributed graph computations. However elasticity has been explored in many other areas.

A. Data Centers

AutoScale [6] enables elastic capacity management for data centers. Its goal is to reduce power wastage by maintaining just enough server capacity for the current workload. [30] proposes solving the same problem using Model Predictive Control framework.

B. Cloud Systems

CloudScale [25] and [13] propose mechanisms to scale-up VM resources based on predicted application needs in an Infrastructure as a Service (IaaS) environment. AGILE [21] proposes mechanisms to scale-out VM resources based on predicted application needs.

C. Storage Systems

[22] proposes social partitioning and replication middleware to enable efficient storage of social network graphs. The technique enables the storage system to scale-out/in based on need. Albatross [4] enables scaling of multi-tenant databases using live migration. TIRAMOLA [28] allows NoSQL storage clusters to scale-out or scale-in by applying Markov Decision Process on the workload using user-provided policies. Transactional Auto Scaler [5] proposes another storage resource scaling mechanism that predicts workload behavior using analytical modeling and machine learning.

D. Data Processing Frameworks

Starfish [10] performs tuning of Hadoop parameters at job, workflow and workload levels. The authors in [9] propose Elastisizer which has the capability to predict cluster size for Hadoop workloads. [3] proposes workload based scheduling of Storm topologies.

E. Partitioning in Graph Processing

PowerGraph [8] performs vertex assignment using balanced partitioning of edges. The aim is to limit number of servers spanned by the vertices. Distributed GraphLab [18] proposes a two-phase assignment of vertices to servers. The first phase creates more partitions than the number of servers. In the second stage, servers load their respective partitions based on a balanced partitioning. This allows the graph to be loaded in a distributed manner and the number of servers to change without affecting the first phase. The authors in [26] discuss partitioning strategies for streaming graph data. However, elasticity is not explored. Using partitioning during a scale-out/in operation is prohibitive as it partitions the entire graph – in comparison, we do incremental repartitioning.

F. Dynamic Repartitioning in Graph Processing

[29] proposes a vertex migration heuristic between partitions, to keep partitions balanced and to reduce communication cost. GPS [24] also proposes dynamic repartitioning of vertices by co-locating vertices which exchange higher more messages with each other. While these works do not explore on-demand elasticity explicitly, our techniques are orthogonal to, and can be applied to systems like the above two. Concretely, our vertex re-partioning technique (Section II-A) can be used in such systems by treating each partition as the set of vertices currently assigned to that server (instead of the hashed set of vertices, as we do).

VIII. Conclusion

In this paper, we have proposed techniques to enable on-demand elasticity operations in distributed graph processing engines. Concretely, we proposed two techniques for deciding what vertices to migrate: Contiguous Vertex Repartitioning (CVR) and Ring-based Vertex Repartitioning (RVR). We also integrated these techniques into the LFGraph graph processing engine, and incorporated several optimizations. Our experiments with multiple graph benchmarks and a real Twitter graph show that: i) compared to the optimal approach, our techniques incurred less than 9% overhead for scale-out and less than 21% overhead for scale-in operations, and ii) our techniques scale well.

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