GX-Plug: a Middleware for Plugging Accelerators to Distributed Graph Processing

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Abstract—Recently, research communities highlight the necessity of formulating a scalability continuum for large-scale graph processing, which gains the scale-out benefits from distributed graph systems, and the scale-up benefits from high-performance accelerators. To this end, we propose a middleware, called the GX-plug, for the ease of integrating the merits of both. As a middleware, the GX-plug is versatile in supporting different runtime environments, computation models, and programming models. More, for improving the middleware performance, we study a series of techniques, including pipeline shuffle, synchronization caching and skipping, and workload balancing, for intra-, inter-, and beyond-iteration optimizations, respectively. Experiments show that our middleware efficiently plugs accelerators to representative distributed graph systems, e.g., GraphX and Powergraph, with up-to 20x acceleration ratio.

Index Terms—Distributed graph systems, Middleware, accelerators

I. INTRODUCTION

Big graph analytics are often with large data volumes, high computation intensiveness, and diversified applications, such as social networks, Internets, traffic networks, and biological structures, just to name a few. To meet the scaling-out challenge [1], an increasing number of distributed graph systems, including GraphX [2] and PowerGraph [3], are proposed and deployed. To meet the scaling-up challenge, non-distributed graph systems, such as Gunrock [4] and ThunderGP [5], incorporate accelerators, including GPUs, multi-core CPUs, and FPGAs. Beyond merely scaling-out or scaling-up, recent research spotlights the vision of a scalability continuum [6], where distributed graph systems and accelerators can be integrated for elastic scaling of big graph systems deployed in data centers.

The high computational concentration in cloud services makes an appealing case for accelerating applications on distributed systems. For example, multi-core processors, like GPUs [7] and multi/many-core CPUs [8], [9], have been deployed as accelerators in distributed instances of cloud services, such as Amazon EC2, Google cloud, Microsoft Azure Blob, and HW cloud, for flexibly scaling up the performance to application demands. Also, Nvidia has announced the plan to support Spark 3.0 with GPU acceleration in 2020 [7], [10]. So, it becomes a natural technology trend for integrating accelerators with distributed graph systems.

However, it is more challenging for distributed graph systems, because there exist a large number of system variants [6], due to the diversity and irregularity of distributed graph processing. They are with different architectures, runtime environments (Java and C++), and computation model [4] and programming model [5]. In this work, we propose a middleware, the GX-Plug, where accelerators can be neatly plugged to heterogenous distributed graph systems. With such a middleware, users can economically scale up their graph systems, to avoid the overhead of replanting to a new accelerator-aided graph systems, and save the efforts of accelerator accessing and subsequent optimizations.

A bird’s eye view of the middleware is shown in Figure 1 which follows an agile framework, called the daemon-agent framework. A daemon is a multi-core processor, an abstract representation of an accelerator, enabling transparent integration of accelerators (GPUs or CPUs), to a distributed graph system (GraphX or PowerGraph), by holding customizable graph programming interfaces. An agent is resided in a distributed node for bridging upper systems and daemons, covering data exchanging and daemon life-cycle controlling. A agent connects one or more daemons, according to the number of accelerators that the system allocates, for flexible computation resource distribution and workload balancing. With the daemon-agent framework, the middleware shows flexibility in supporting different runtime environments, computation models, and programming models.

For easy accessing to accelerators, daemon provides a graph algorithm template, based on conventional iterative models, and support transplanting existing distributed graph algorithms with ease. Agent provides a kit of interfaces to cooperate with

1BSP (Bulk Synchronous Parallel) is a parallel model that performs computation in iterative steps, including three steps of computation, communication, and synchronization. BSP model [11] has been the most fundamental and popular execution approach on distributed graph systems. GAS (Gather-Apply-Scatter) model [5] is another basic and widely adopted model for distributed graph processing, based on BSP [12].

2It includes vertex- and edge-centric models [13].
daemons and uppers systems for global graph computation. Accordingly, it takes only a few lines of code to plug accelerators to upper systems.

Nevertheless, there arise a series of research challenges for implementing the middleware, besides the software design and development efforts on the adaption to different runtimes (Java or C++) and different accelerators (GPUs or CPUs). First, there exists considerable data transmission overhead for the middleware in delivering and translating the data payloads into desired formats, between upper systems and accelerators, causing intra-iteration overhead. Second, the irregular and complex graph structure incurs imbalanced workloads, as well as latencies in frequent global synchronization, causing inter-iteration overhead. Third, it is difficult to schedule the workload and computation resource for different tasks and system configurations, recognized as beyond-iteration overhead. The overheads can much degrade the middleware performance.

We tackle the first challenge by incorporating pipeline shuffle for optimizing the data transferring between daemons and agents. We tackle the second challenge by optimizing the process of data synchronization, including caching and skipping, so as to minimize the volumes of data transferring during the synchronization phase. We tackle the third challenge by making the size of transferred data blocks self-adaptive to the workloads of distribute nodes, and therefore the system workload balancing can be improved.

In this work, we focus on the implementation and optimization of the middleware. We are aware of optimization techniques, either on the accelerator end, e.g., exploring memory hierarchies for accelerating on-chip data accessing or reinforcing local GPU processing networks with NVLink and NVSwitch; or on the upper system end, e.g., using RDMA for faster distributed system communication and using pull-push model for data transferring optimization in specific applications. We would like to argue that optimizations merely on upper system or accelerator end are beyond the scope of the middleware, and are orthogonal to our work.

Our contributions can be listed as follows.
- We propose, to our best knowledge, the first middleware for arming distributed graph systems with high-performance accelerators, to meet the needs of scaling-out and -up in big graph analytics.
- For the middleware, we design a novel daemon-agent framework, which achieves flexible deployment on different upper systems and easy accessing to accelerators.
- The middleware is general in supporting different computation models, such as BSP and GAS. Existing distributed graph algorithms can be transplanted for accessing accelerators with ease.
- For the middleware optimization, we investigate a series of techniques, such as pipeline shuffling, synchronization caching and skipping, and workload balancing, for intra-, inter-, and beyond-iteration optimizations, respectively.
- We conduct extensive experiments on real datasets to evaluate the efficiency and scalability of the middleware.

The rest of the paper is organized as follows. Section II shows the overview of the middleware. Section III investigates optimization techniques used to improve the internal performance of middleware. Section IV discusses middleware deployment techniques. Section V reports the results of empirical studies. Section VI presents related works. Section VII concludes the paper. Our middleware is open sourced.

II. MIDDLEWARE OVERVIEW

Cloud services are witnessed to evolve from cloud storage services, comprised of a multitude of distributed nodes/machines/instances, to high-performance cloud computing services, comprised of accelerator-powered distributed nodes, as aforementioned. Our middleware is to boost graph computing on such cloud services, supporting system configuration and application development with ease. In this section, we investigate the daemon-agent framework, which is the core of the middleware, in Section II-A. Then, we study the data storage and the controllers of the middleware, in Sections II-B and II-C respectively.

A. Daemon-Agent Framework

The structures of daemons and agents, and their interactions are shown in Figure 2. In general, daemons are in connection with accelerators, and agents are in connection with upper systems. The communication of the two parts is done via the System V IPC.

![Fig. 2: Daemon-Agent Framework](https://thoh-testarossa.github.io/GX-Plug/)

1) Daemon: A daemon represent an accelerator, where graph algorithms are executed. A daemon thus holds an algorithm template and the iteration logic controlling, as shown in Figure 2. The design of a daemon is towards transparent hardware management for upper systems. At the runtime, an instance of the algorithm template is implemented for daemons. For accelerating distributed graph algorithms, algorithm engineers only focus on the implementation of the APIs of the algorithm template. The connection with accelerators are established during the initialization phase, and details are hidden to system developers after that.

2) Agent: An agent represent a distributed node of an upper system and makes a bridge for upper systems and daemons. Essentially, an agent covers a set of operation interfaces between upper systems and daemons, on data exchanging, subfunction execution, and daemon lifecycle controlling. With

3https://thoh-testarossa.github.io/GX-Plug/
the operation interfaces on agents, upper systems can substantially configure and control daemons, including specifying the number of accelerators and mixing and matching different types of accelerators in a system. The structure of an agent is shown in Figure 2.

In the local environment of a distributed node, there should be at least one agent, and one or more daemons, representing different accelerators. Also, as shown in Section III, agents are equipped with a series of optimization techniques to reduce the overhead caused by data transferring, which is the major source affecting system performances.

B. Data Flows & Management

The challenges in the data management of the middleware are two-fold: 1) upper systems and accelerators can be of different runtime environments (C++ and Java); 2) data in different upper systems may follow different (vertex- or edge-centric) storage strategies. More, the data transferring should be efficient in order to meet the system runtime requirements.

The data flow in the middleware is shown in Figure 3. To tackle the efficiency challenge, the graph data is neither stored in the agent side, nor in the daemon side. Instead, data is stored in the shared memory space based on the System V IPC.

![Fig. 3: Data Flows & Management](image)

Initially, the graph data are partitioned to distributed nodes by upper systems. Then, for each distributed node, the data are fed to daemons for acceleration via agents. However, data accessed by an agent cannot be directly accessed by a daemon, since they belong to different processes with no common memory space, as discussed in Section IV-C. More, conventional inter-process communication incurs extra data transferring, degrading the system runtime performance. In our implementation, we use kernel functions aided by the UNIX System V to create a shared memory space for daemons and agents. In our middleware, a daemon has a unique System V key pointing to its specific shared memory space, while an agent has multiple keys to communicate with all daemons attached to it.

The benefits are on three aspects. First, the common shared memory space enables the mutual data accessing between upper systems and accelerators that are of different environments. Second, data accessing can be done via the common memory space, avoiding the intermediate data copying between the two ends. Third, any data updates in the agent or daemon end can be immediately perceived by the other end without extra sensing efforts, thus facilitating the control logic of the system.

For efficient processing in accelerators, a daemon uses a series of data blocks, including vertex blocks and edge blocks, to be fed to accelerators. Each edge block contains a fixed number of edges. Also, each edge block is associated with a paired vertex block, where both source and destination vertices of an edge can be found. There is a vertex-edge mapping table, for transforming the data stored in the vertex and edge tables of the agent end to the vertex and edge blocks of the daemon end. Thus, to construct an edge block, an agent selects a vertex and retrieves its outer edges, with vertex-edge mapping table. The corresponding vertex block is constituted by incorporating destination vertices, as well as their attributes, for the edges in the edge block.

So, at each iteration of computation, the middleware packages up the vertex and edge blocks for accelerators, by repeatedly selecting vertices or edges that are needed. After an iteration of computation, updated vertex and edge blocks are synchronized back to the vertex and edge tables.

C. Controllers

For the middleware, daemons are in charge of orchestrating different computational components. We introduce two components located in the daemon, making the middleware adaptable to different computation models and optimizing the iterative processing for upper systems.

1) Runtime Control: The runtime control component is for controlling the execution order of implemented APIs, including the runtime information collected from accelerators and sending/receiving flags for iteration controlling. By controlling the execution order of implemented APIs, the middleware can easily be integrated into different computation models, as discussed in Section IV-B2.

2) Iteration Control: The iteration control component is for controlling and coordinating the entire iteration. Since the middleware separates the runtimes of upper systems and the computation, it is necessary to connect both parties for in-between data synchronization and the computation processing cycle. Several optimizations, such as pipeline shuffling, synchronization caching, and skipping, are implemented in Section III. The component collaboratively works with agents for retrieving information from upper systems, and works with the runtime control component for exchanging flag information, to fulfill the iteration controlling.

The main goal of the middleware is to shield the system developers and graph algorithm programmers from the het-
erogeneity in different systems and accelerators. It is achieved at the expense of internal overheads in the middleware. In the sequel, we devise a series of optimizations to alleviate or even eliminate the overhead originating from the middleware.

III. Runtime Optimization

In this section, we introduce three optimization techniques, pipeline shuffling for improving intra-iteration processing, synchronization caching and skipping for eliminating unnecessary data transferring for inter-iteration processing, and workload balancing for beyond-iteration optimization.

A. Intra-Iteration Optimization: Pipeline Shuffling

1) Motivation: For the basic daemon-agent framework aforementioned, an ordinary workflow of graph processing acceleration consists of five steps, data downloading (from upper systems), agent-to-daemon data transferring, computing, daemon-to-agent data transferring, and data uploading (to upper systems). However, a tightly coupled execution of the five steps, where the output of one step is streamed as the input of another step, leads to many waiting-and-suspending states and therefore the underutilization of computation resources.

For example, the computing step must wait for agent-to-daemon data transferring to start, so that the computing step would be suspended during other steps. To alleviate the predicament and to improve the computation resource utilization, we investigate a pipeline parallelism mechanism, Pipeline shuffle, to the middleware.

![Fig. 4: Pipeline Shuffle](image)

**Algorithm 1 Pipeline Shuffle - Daemon Side**

**Input:** Computer Device com_dev, Data area pointer n, c, u

1. while In Iteration do
2. Block_Recc(agent, msg)
3. if msg = “ExchangeFinished” then
4. Rotate(n → c → u → n)
5. Send(agent, “RotateFinished”)
6. else if c contains contents to compute then
7. com_dev.Load(c)
8. com_dev.Compute()
9. *c ← com_dev.data
10. Send(agent, “ComputeFinished”)
11. else
12. Send(agent, “ComputeAllFinished”)
13. End_Iteration()

2) Overview: The idea is to construct a multi-layer pipeline for better parallelism. First, we replace the original 5-step data transferring into a 3-step data transferring, data downloading, computing, and data uploading, which are handled by 3 threads, Thread.Download, Thread.Compute and Thread.Upload, respectively. Compared to the 5-step setting, the 3-step setting eliminates the two steps of agent-to-daemon and daemon-to-agent data transferring. Second, based on the 3-step setting, we construct a 3-layered pipeline to reduce the suspension time of the computing step, and finally improve the accelerator utilization. The overview of pipeline shuffle is shown in Figure 5. The detailed process is depicted by Algorithms 1 and 2.

   a) Pipeline Parallelism: The pipeline consists of 3 layers in correspondence to the 3 steps mentioned above, as shown in Figure 5. With the pipeline, an iteration can be decomposed into a sequence of 3 processing cycles, corresponding to the 3 layers. For all three pipeline layers, we use “edge triplets” as the intermediate data structure, which includes an edge and its source and destination vertices, by efficiently joining the edge and vertex tables. With the data structure of edge triplets, the pipeline has homogenous data structures for all layers, for avoiding unnecessary data format transformation and enabling granular-granularity data retrieval. Essentially, the triplet is the basic processing unit of an iteration, which serves as both the source of computation input and the carrier of output. Within an iteration, there is no data dependencies between triplets.

   For each layer, triplets are grouped into a set of blocks, as shown in Figure 5. The blocks are assigned to the 3 threads for processing. Thus, pipeline parallelism can be established which significantly improves the system performance.

![Fig. 5: Pipelined Process Flow with Pipeline Shuffle](image)
data layer stores the result of \( i \)-th pipeline process cycle, and is used for \((i+1)\)-th downstream pipeline process cycle. Within a cycle, data are transferred between threads for fulfilling the processing. However, frequent data copying incurs considerable system overhead.

To handle that, we design a shuffle mechanism for efficient data transferring in pipeline parallelism. First, we allocate equal sized memory chunks for threads. Each memory chunk is associated with a pointer, for the reference of the front block currently being processed inside the chunk. Second, inter-thread data copying is replaced by the pointer copying. For example, in Figure 3 data blocks of 3 layers can be represented by \( n \)-block, \( c \)-block, and \( u \)-block, indicating blocks for new data retrieved from upper systems, blocks for computing, and blocks for uploading to upper systems, respectively. When a pipeline cycle is finished, the 3 pointers are shuffled in a rotation manner: the pointer to \( n \)-block switches to \( c \)-block, the pointer to \( c \)-block switches to \( u \)-block, and so on. With the pipeline shuffle mechanism, there is no more data copying between threads, since it is completed in situ.

c) Block Size Selection: In our work, we found the size of a block has a profound effect over the parallelism performance. We assume that there is a sub-dataset distributed to a agent-daemon pair for processing which contains \( d \) entities need to be processed in the current iteration. Also, agent divides the dataset into \( s \) blocks evenly, \( b = \frac{d}{s} \). Let \( T_n(b), T_c(b), T_u(b) \) be the process time of one data block in Thread.Download, Thread.Compute and Thread.Upload, respectively. \( T_n \) and \( T_u \) are proportional to the data size. We can estimate pipeline processing time \( T_{total} \).

\[
T_{total} = T_n(b) + \max(T_c(b), T_u(b)) + (s-2)\max(T_n(b), T_c(b), T_u(b)) + \max(T_c(b), T_u(b)) + T_n(b)
\]

\( T_c \) refers to the time cost of Thread.Compute, and consists of calling computation devices, loading data to devices, and computation. Their corresponding time costs are represented by \( T_{call} \), \( T_{comp} \), and \( T_{copy} \), respectively. The operation of calling devices takes constant time, while computation and data copying time are related to data size. So, \( T_c(b) \) can be modeled as follows.

\[
T_c(b) = T_{call} + T_{comp}(b) + T_{copy}(b)
\]

When \( s \) increases, block size \( b \) decreases, so do \( T_n \) and \( T_u \). \( T_c \) also decreases when \( b \) decreases, but will never be less than \( T_{call} \), which means \( T_{total} \) starts increasing when \( s \) is large enough and keep increasing. On the other hand, \( T_n \) and \( T_u \) increase when \( s \) is smaller, since \( b \) is being larger. Thus, both the function \( T_{total}(b) \) and \( T_{total}(s) \) should tend to become a U-turn form. Thus, \( s \) and \( b \) should be deliberately configured for achieving fine-tuned system performance. We will try to calculate the value of \( b \) in order to provide optimization suggestion to overall system.

The calculation follows two assumptions: 1) The sub-dataset distributed to the agent-daemon pair has \( d \) entities, and is divided into \( s \) blocks evenly, which have the size \( b = \frac{d}{s} \). 2) We assume that there is a sub-dataset distributed to an agent-daemon pair has \( d \) entities, and is divided into \( s \) blocks evenly, which have the size \( b = \frac{d}{s} \). We also assume that there is a sub-dataset distributed to the agent-daemon pair has \( d \) entities, and is divided into \( s \) blocks evenly, which have the size \( b = \frac{d}{s} \) we

\[
T_{total} = k_1b + \max(k_1b, a + k_2b) + (s-2)\max(k_1b, a + k_2b, k_3b) + \max(a + k_2b, k_3b) + k_3b
\]

Lemma 1 shows the derivation of optimal \( b \) for the pipeline shuffle mechanism, as follows.

**Lemma 1.** If a distributed node stores \( d \) data entities, the optimal block size \( b_{opt} \) and corresponding \( T_{total\_{min}} \) can be calculated as follows, where \( Q = \sqrt{\frac{ad}{k_1-k_2}} \).

\[
b_{opt} = \begin{cases} 
\frac{a}{k_1-k_2} & \text{if } k_{max} = k_1, \frac{a}{k_1-k_2} < Q \\
\frac{a}{k_3-k_2} & \text{if } k_{max} = k_3, \frac{a}{k_3-k_2} < Q \\
\frac{ad}{k_1+k_3} & \text{otherwise}
\end{cases}
\]

\[
T_{total\_{min}} = \begin{cases} 
\frac{a(k_1+k_3)}{k_1-k_2} + k_3d, & \text{if } k_{max} = k_1, \frac{a}{k_1-k_2} < Q \\
\frac{a(k_1+k_3)}{k_3-k_2} + k_3d, & \text{if } k_{max} = k_3, \frac{a}{k_3-k_2} < Q \\
k_2d + 2\sqrt{(k_1+k_3)ad}, & \text{otherwise}
\end{cases}
\]

**Proof.** Following Equation 2, we have 3 cases to consider.

**Case 1:** \( T_n = k_1b \) is the maximum value. This case is true only if \( k_1 \) is the maximum of the 3 parameters, \( k_1, k_2, \) and \( k_3 \). Accordingly, \( b \) should satisfy the follows.

\[
k_1b \geq a + k_2b \Rightarrow b \geq \frac{a}{k_1-k_2}
\]

Thus, Equation 2 can be transformed into:

\[
T_{total} = sk_1b + \max(a + k_2b, k_3b) + k_3b = k_3d + \max(a + k_2b, k_3b) + k_3b
\]

Notice that \( a \) and \( \{k_i\}_{i=1}^3 \) are all positive, and both \( \max(a + k_2b, k_3b) \) and \( k_3b \) increase when \( b \) increases. Thus, when \( b = \frac{a}{k_1-k_2} \), we have the minimum value of \( T_{total} \) as follows.

\[
T_{total} = k_1d + \max(a + \frac{a \cdot k_2}{k_1-k_2}, \frac{a \cdot k_3}{k_3-k_2}) + \frac{a \cdot k_3}{k_1-k_2}
\]

\[
= k_1d + \max(\frac{a \cdot k_2}{k_1-k_2}, \frac{a \cdot k_3}{k_3-k_2}) + \frac{a \cdot k_3}{k_1-k_2} = k_1d + \frac{(k_1+k_3)a}{k_1-k_2}
\]

**Case 2:** \( T_c = (a + k_2b) \) is the maximum value. First, we have this equation below, where \( s = \frac{d}{b} \).

\[
T_{total} = k_1b + s(a + k_2b) + k_3b = (k_1 + k_3)b + k_2d + \frac{ad}{b}
\]
In this situation, we can have the minimum $T_{total}$, if $b$ equals $\sqrt{\frac{ad}{k_2}}$, which is $Q$. Notice that $b$ may not equal $Q$, as constrained by $\{k_i\}$. Accordingly, we discuss $T_{total}$ in 3 subcases, based on the value of $k_2$.

$k_2$ is the minimum one. In this situation, both $(k_1 - k_2)$ and $(k_3 - k_2)$ are positive. Thus, we have:

$$a + k_2 b \geq \max(k_1, k_3) \cdot b \Rightarrow b \leq \min\left(\frac{a}{k_1 - k_3}, \frac{a}{k_3 - k_2}\right)$$

Assume that $k_1 \geq k_3$, we have $b \leq \frac{a}{k_1 - k_3}$. Thus, we have the minimum $T_{total}$:

$$T_{total} = \begin{cases} k_2 d + 2\sqrt{(k_1 + k_3)a}d, & \frac{a}{k_1 - k_3} \geq Q \\ \frac{a}{k_1 - k_2} + k_2 d + (k_1 - k_2)d, & \frac{a}{k_1 - k_2} < Q \end{cases}$$

Also, we have the minimum $T_{total}$ when $k_3 \geq k_1$:

$$T_{total} = \begin{cases} k_2 d + 2\sqrt{(k_1 + k_3)a}d, & \frac{a}{k_3 - k_2} \geq Q \\ \frac{a}{k_3 - k_2} + k_2 d + (k_3 - k_2)d, & \frac{a}{k_3 - k_2} < Q \end{cases}$$

$k_2$ is the middle one. In this situation, we should notice the change of the inequality, because some terms of Equation 4 can be negative. Without loosing generality, we assume $k_3 \leq k_2 \leq k_1$. In this case, $(k_1 - k_2)$ is positive, and $(k_3 - k_2)$ is negative. Thus, we can have $b \leq \frac{a}{k_1 - k_2}$, since

$$\frac{a}{k_3 - k_2} < 0 \leq b \leq \frac{a}{k_1 - k_2} \Rightarrow 0 \leq b \leq \frac{a}{k_1 - k_2}$$

Then, we have the minimum value of $T_{total}$ as shown in Equation 4.

$$T_{total} = \begin{cases} \frac{a(k_1 + k_3)}{k_1 - k_2} + k_2 d + (k_1 - k_2)d, & \frac{a}{k_1 - k_2} < Q \\ k_2 d + 2\sqrt{(k_1 + k_3)a}d, & \text{otherwise} \end{cases}$$

On the other hand, if $k_3 \geq k_2 \geq k_1$ holds, the minimum value of $T_{total}$ is:

$$T_{total} = \begin{cases} \frac{a(k_1 + k_3)}{k_3 - k_2} + k_2 d + (k_3 - k_2)d, & \frac{a}{k_3 - k_2} < Q \\ k_2 d + 2\sqrt{(k_1 + k_3)a}d, & \text{otherwise} \end{cases}$$

$k_2$ is the middle one. In this situation, both $k_1 - k_2$ and $k_3 - k_2$ are negative. Since $b > 0$, $b$ is also greater than $\frac{a}{k_1 - k_2}$ and $\frac{a}{k_3 - k_2}$. Thus, we have the minimum $T_{total} = k_2 d + 2\sqrt{(k_1 + k_3)a}d$, when $b = \sqrt{\frac{ad}{k_1 + k_3}} = Q$.

Case 3: $T_u$ is the maximum value. This case is true only if $k_3$ is the maximum of the 3 parameters in $k_1$, $k_2$, and $k_3$.

Following the discussion in Equation 4, we simply have the conclusion that $T_{total}$ has the minimum value $k_3 d + \frac{(k_1 + k_3)a}{k_3 - k_2}$ when $b = \frac{a}{k_3 - k_2}$.

Discussion. Following the previous discussion, and the order of $k_1$, $k_2$ and $k_3$, we have 3 cases to calculate $b_{opt}$.

Case (i). $k_1$ is the maximum one: if $\frac{a}{k_1 - k_2} \geq \sqrt{\frac{ad}{k_1 + k_3}} = Q$, $b = \sqrt{\frac{ad}{k_1 + k_3}} = Q$, and $T_{total}$ have the minimum value $k_2 d + 2\sqrt{(k_1 + k_3)a}d$. Otherwise, $b = \frac{a}{k_3 - k_2}$, and $T_{total}$ have the minimum value $k_1 d + \frac{(k_1 + k_3)a}{k_3 - k_2}$.

Case (ii). $k_2$ is the maximum one: $b = \sqrt{\frac{ad}{k_1 + k_3}} = Q$, and $T_{total}$ have the minimum value $k_2 d + 2\sqrt{(k_1 + k_3)a}d$.

Case (iii). $k_3$ is the maximum one: if $\frac{a}{k_3 - k_2} \geq \sqrt{\frac{ad}{k_1 + k_3}} = Q$, $b = \sqrt{\frac{ad}{k_1 + k_3}} = Q$, and $T_{total}$ have the minimum value $k_3 d + \frac{(k_1 + k_3)a}{k_3 - k_2}$.

Then, Equations in Lemma[1] can be directly derived from the above discussion, by grouping $b$ and $k$.

Notice that both $s$ and $b$ must be integers. If $s_{opt}$ or $b_{opt}$ is not an integer, we choose 2 values $\lfloor s_{opt} \rfloor$ and $\lceil s_{opt} \rceil$ for $s$, and 2 values $\lfloor b_{opt} \rfloor$ and $\lceil b_{opt} \rceil$ for $b$, so that Equation 2 can be used for estimating the minimum $T_{total}$.

B. Inter-Iteration Optimization: Synchronization Caching and Skipping

1) Motivation: For a distributed graph system, there is inevitable data synchronization between iterations, for ensuring the data correctness in every distributed node. However, it is often costly to do such synchronizations, since it would trigger considerable data copying between two successive iterations. Also, in a naively integrated scale-out and -up system, the data copying involves memory accessing from distributed system environments to external computation accelerators, which is costly. Thus, it is necessary to reduce the load of data synchronization, either for the number of times that synchronization triggers, or for the data volume transferred. To this end, we introduce techniques of synchronization caching and synchronization skipping for inter-iteration optimization.

2) Synchronization Caching: Figure 6 shows the main process of synchronization caching. The idea is to use local cache of agents to reduce unnecessary data transferring between daemons and upper systems. It has two parts, LRU-based caching and lazy uploading.

a) LRU-based Caching: Think twice about the data transferring process. At the beginning of an iteration, an agent downloads data to be computed from upper systems. A vertex would have to be repeatedly downloaded from upper systems, if it is involved in the computation iterations, even though its corresponding attributes are never updated.

To save the overhead, the agent can cache a set of vertices in a temporary vertex table, and the cache is organized in an LRU (least recently used) manner. Initially, when entering the cache, every vertex has a weight, whose value decreases with the passage of iterations, and increases if
being used for computation. When the daemon requires a specific vertex for computation, the agent first checks its local cache for the vertex. If not found, the agent downloads it from upper systems to cache, and evicts the vertex with the highest weight. When the agent collects computation results for updating to upper systems, it first checks if corresponding vertices are cached. If so, the agent updates the attributes of the vertex, and upgrades its weight. Otherwise, the agent chooses vertices with the lowest weights, and replaces them by vertices in the computation result. If the chosen vertices were updated in previous iterations, corresponding information will be uploaded to upper systems. The updated vertices in the cache are marked, for lazy uploading, as discussed below.

b) Lazy Uploading: Also, there is no need for immediately uploading an updated vertex, until it is involved in the computation of other distributed nodes. For example, if there are many copies of a vertex generated before the synchronization, only the vertex copy with optimal updated value needs to be uploaded, meaning that other vertex copies are obsolete. Thus, to prevent unnecessary uploading, we make the strategy of “lazy uploading”.

So, we design two queues for the lazy uploading, global query queue and global data queue. After all computation results are updated to the cache, the agent first constructs a list of vertex IDs which are needed by the distributed nodes for the next iteration. Then, all agents push their local lists to the upper system. The union of local lists formulates the global query queue and is broadcast to all agents. Each agent compares its cache with the global query queue, and uploads the required vertices to the global data queue. This way, data uploading is triggered only if necessary. Algorithm 3 shows the details of lazy uploading.

Algorithm 3 Lazy Uploading

Input: Updated Dataset \( s \), Global query queue \( gqq \), Global data queue \( gdq \)

1: \( s_q \leftarrow s.\text{GetQueriedEntity()} \)
2: Send\( (gqq, s_q) \)
3: Wait for other agents
4: \( s_u \leftarrow \text{Find}(gqq, s.\text{GetUpdatedEntity}()) \)
5: Send\( (gdq, s_u) \)
6: Wait for other agents and upper system synchronization
7: \( s.\text{Update}(\text{Fetch}(gdq, s_q)) \)

3) Synchronization Skipping: Following the characteristics of distributed graph processing, it happens that some iterations can be skipped, so that the synchronization overheads of these iterations can be saved. The observation is that, there is no need to trigger the global synchronization, if there is no de facto “conflicts” among distributed nodes for being synchronized, i.e., updated data of a node is not needed by all other nodes. We therefore design a mechanism called “synchronization skipping” based on synchronization caching, to detect if the current iteration synchronization can be skipped.

As shown in Figure 7 at the end of cache updating, an agent checks if each updated vertex and its outer edges are in the same node. If it is true for an agent, it means the agent can continue with the next iteration using its local data. If it is true for all agents, it means that there is no need for any inter-node data transferring. Thus, the upper system process can be skipped and next computation iteration can be directly started. This way, multiple computation iterations can be equivalent to a logically combined iteration, and therefore unnecessary synchronization for intermediate iterations can be skipped.

C. Beyond-Iteration Optimization: Workload Balancing

1) Motivation: As a “software glue”, the middleware connects different accelerators and different upper systems. For instance, upper systems may adopt various graph partitioning strategies for assigning subgraphs to distributed nodes, which may cause storage imbalance. On the other hand, different accelerators may have different computation powers, which may cause computation imbalance. Therefore, it is important for the middleware to have a mechanism to detect and react to the workload balancing, so that the performance of the parallelism can be maximized.

2) Analysis: To this end, we introduce a simple yet effective workload estimation model for the middleware to predict the performance of data processing of a local node.

Suppose there are in total \( D \) data entities which are partitioned into \( m \) distributed nodes, satisfying \( \sum_{j=1}^{m} d_j = D \). According to pipeline shuffle mechanism in Section III-A, the total processing time consists of three parts. For ease of discussion, for distribute node \( j \), we set the total time cost \( T_{\text{total}} \) taken by Thread.Download, Thread.Compute, and Thread.Upload as \( T^{j}_{\text{d}}, T^{j}_{\text{c}}, \) and \( T^{j}_{\text{u}} \), respectively, satisfying \( T_{\text{total}} = T^{j}_{\text{d}} + T^{j}_{\text{c}} + T^{j}_{\text{u}} \). Noted that both \( T^{j}_{\text{d}} \) and \( T^{j}_{\text{u}} \) are proportional to \( d_j \), \( T^{j}_{\text{c}} \)’s computation time and data copying time are also proportional to \( d_i \), and calling time \( T^{j}_{\text{call}} \) is proportional to the number of blocks \( s \). We can have:

\[
T_{\text{total}} = T^{j}_{\text{d}} + T^{j}_{\text{c}} + T^{j}_{\text{u}} = c_j \cdot d_j + s \cdot T^{j}_{\text{call}},
\]

where \( c_j \) is the coefficient associated with node \( j \) to represent the relation between data size and process time. Since there is no relationship between \( s \) and \( d_j \), there is no need to consider \( s \) in this situation. Then, given a set of \( m \) distributed nodes, the objective of workload balancing can be represented by:

\[
\min\left(\max_{j \leq m}(c_j \cdot d_j)\right)\quad (5)
\]

Here, we call \( \frac{1}{c_j} \) as computation capacity factor, since \( c_j \) shows “time cost per unit amount of data”, and \( \frac{1}{c_j} \) shows “data processed per unit time".
Lemma 2. Given $D$ data entities which are partitioned to $m$ distributed nodes, where each node holds a data fragment $d_j$, satisfying $\sum_{j=1}^m d_j = D$, the balancing target is to minimize function $G(\cdot)$, which represents the maximum time cost of a distributed node.

$$G(d_1, ..., d_m) = \max_{j=1...m} (c_j d_j)$$

It holds that function $G(\cdot)$ achieves its minimum value, if every element $d_j$ of its $m$-dimensional input variable $\{d_j\}_{j \leq m}$ satisfies:

$$d_j = \frac{\frac{1}{c_j}}{\sum_{j=1}^m \frac{1}{c_j}} D$$

Proof. First, if every $d_j$ meets the condition, we have:

$$G(d_1, ..., d_m) = \max_{j=1...m} \left\{ c_j \cdot \frac{\frac{1}{c_j}}{\sum_{j=1}^m \frac{1}{c_j}} D \right\} = \frac{D}{\sum_{j=1}^m \frac{1}{c_j}}$$

Second, we prove that for any possible $d_j$, we have $G \geq \frac{D}{\sum_{j=1}^m \frac{1}{c_j}}$. We prove this assertion by contradiction. We first assume it holds that $G = \max_{j=1...m} (c_j d_j) < \frac{D}{\sum_{j=1}^m \frac{1}{c_j}}$. Then for every $d_j$, we have:

$$d_j < \frac{\frac{1}{c_j}}{\sum_{j=1}^m \frac{1}{c_j}} D \Rightarrow D = \sum_{j=1}^m d_j < \sum_{j=1}^m \frac{1}{c_j} D = D$$

Here, contradiction occurs. Thus, function $F$ reaches the minimum value $\frac{D}{\sum_{j=1}^m \frac{1}{c_j}}$, if and only if for all $d_j$, $d_j = \frac{\frac{1}{c_j}}{\sum_{j=1}^m \frac{1}{c_j}} D$. The lemma is hence proved.

Lemma 3. Given $D$ data entities which are partitioned to $m$ distributed nodes, where each node holds a data fragment $d_j$, satisfying $\sum_{j=1}^m d_j = D$, and given the maximum available computation capacity factor $f$ ($f \geq \max_{j=1...m} \frac{1}{c_j}$), our target is to minimize function $G'(\cdot)$, which indicates the maximum time cost of a distributed node.

$$G'(\frac{1}{c_1}, ..., \frac{1}{c_m}) = \min_{j=1}^m (c_j d_j)$$

Function $G'(\cdot)$ achieves its minimum value, if every element of its $m$-dimensional input variable $\{\frac{1}{c_j}\}_{j \leq m}$ satisfies:

$$\frac{1}{c_j} = f \cdot d_j, \quad \text{where } d_* = \max_{j \leq m} (c_j d_j)$$

Proof. Let $\frac{1}{c_\ast} = \max_{j \leq m} \frac{1}{c_j}$. Since $\frac{1}{c_j} \leq f$, we have:

$$\frac{d_\ast}{f} \leq c_j d_* \leq \frac{d_\ast}{f} = \max_{j=1}^m (c_j d_j)$$

To make $G' = \frac{d_\ast}{f}$, all other $c_j d_j$ must be not greater than $\frac{d_\ast}{f}$. Thus, to minimize $\frac{1}{c_j}$, we have:

$$\frac{1}{c_j} = \min \left\{ \frac{1}{c_j} \right\} \text{ where } c_j d_j \leq \frac{d_\ast}{f} = \frac{f d_j}{d_*}$$

Thus, the lemma is proved.

According to Lemma 3, the middleware can dynamically allocate idle accelerators to generate more daemons for the node demanding computation powers, as long as conditions of computation capacity factor of each partition are met.

IV. SYSTEM IMPLEMENTATION

We show details on key implementation of the middleware.

A. APIs

It is important for the middleware to create a series of easy-to-use interfaces to make accelerators plugged to upper systems easy and coder-friendly. In our implementation, we design an iteration-based graph algorithm template and a set of operations interfaces to connect with upper systems.

1) Algorithm Template: The APIs of algorithm template follow a unified iterative model and support C++-based code integration, including OpenMP, OpenCL, MPI, and CUDA. There are 3 steps with computation of an iteration for general multiworker systems, Message Passing, Combining and Aggregating, in which external computation resources can be utilized for computation optimization. In correspondence to the above 3 steps, our algorithm template has 3 APIs, MSGGen(), MSGMerge() and MSGApply(). MSGGen() function is the computation function for calculating the initial results with vertex and edge blocks and transforming them into initial messages. MSGMerge() function delivers the initial messages to corresponding graph partitions. MSGApply() fetches message sets for the current partition, and applies them to corresponding vertices and edges. Accordingly, one can design a graph algorithm by implementing the 3 interfaces of the algorithm template. Examples of implementing graph algorithms can be found in our code repository.
With the help of the daemon-agent framework, runtime details, such as data transferring, runtime orders, interactions with upper systems, and extra resource management, are hidden to algorithm engineers, thus they can focus on the implementation of three APIs for specific graph algorithms.

More, with the separate maintenance of these functions, upper system developers can arrange the API calls in different orders, so that the middleware is adaptable to various graph computation models, such as BSP, GAS, and asynchronous model, as shown in Section [IV-B2].

2) Operation Interfaces: To make upper system calls easier to be adapted to agents, the agent accessing is organized into three functions, including two functions for data transferring, i.e., transfer() and update(), and function requestX() for computation lifecycle controlling. Here, X can be any of the three APIs, MSGGen(), MSGMerge() or MSGApply(). For an upper system, a call sequence of a computation iteration is: connect() → update() → {requestX()} → update() → disconnect(). Upper system developers only need to access corresponding functions by inputting proper parameters to get the full control of the daemon runtime. Also, it takes merely a few lines of code for the agent to connect to upper systems.

In summary, with such interface functions of agents, computation daemons can be integrated and cooperated for the global computation invoked by upper systems.

B. Environment Accessing

1) GraphX (JVM): JVM is a uniform environment separated from the local environment of distributed nodes to execute Java programs. However, it makes things complicated when GraphX needs external tools or libraries for computation. JNI provided in JVM suffers from additional costs in invoking native target functions, due to JNI callbacks, which can be eased by the native memory [23]. To solve the problem, we design 2 components to efficiently break the barrier between the JVM runtime and local environment.

JNI Transmitter. We use JNI to achieve reflection between GraphX native method interfaces and external functions connected with agent. However, naively invoking JVM methods at runtime incurs significant transmission lags. Hence, we utilize a series of techniques such as POSIX-based shared memory data exchanging, batch data transferring, in JNI transmitter in order to reduce JNI calls.

Data Packager. Data packager solves the inconsistency of data structures of the two ends of JVM and local environment. It uses techniques of bit data organization and space reserving for data transformation without extra space usage and redundant data copying. Preliminary testing shows that about 3 to 10 times of improvement can be achieved, compared to direct target function invoking.

2) PowerGraph: PowerGraph [3], follows another computation model, called Gather-Apply-Scatter (GAS in short), which is widely used by many distributed graph processing frameworks. Although BSP and GAS are of different graph computation models, they are common in basic iterative characteristics [13], which can be view as different orders of iterative operations, etc. It paves the road for theoretical and technical foundation of a general middleware design in supporting different computation models.

For example, when connecting to PowerGraph, MSGGen(), MSGMerge() and MSGApply() is used to represent scatter, gather, and apply steps in GAS model. The execution order in PowerGraph thus follows Merge() → Apply() → Gen(), which differs from BSP model, i.e., Gen() → Merge() → Apply(). In an iteration, PowerGraph calls agent interfaces, in the order of requestMerge(), requestApply() and requestGen(), so that GAS model can be supported by the middleware without any extra code modifications. It shows the generality of our middleware in adapting to different computation models.

C. Runtime Isolation

If an agent is naively designed as a parent process of daemons, the device environment of accelerators would be re-initialized multiple times during the iterative graph processing. Because the launching and ceasing of an agent must be triggered multiple times by the upper system, and so do their associated daemons. The frequent re-initialization incurs considerable system overheads, since the initialization process of daemons (with internal function calls) and associated computational devices is time-consuming. To overcome the dilemma, our daemon-agent framework detaches the initialization process from direct function calls. Daemons and agents work as independent processes, and they communicate with each other by message exchange. This way, a daemon never triggers re-initialization during the iterative graph processing.

V. EVALUATION

A. Setup

We conduct experiments on a set of representative graph algorithms, such as Bellman-Ford (SSSP-BF), PageRank (PR), and Label Propagation algorithm (LP), by varying datasets of different distributions and scales. For experiments, we use a series of 6 real datasets which are commonly used for graph systems testing, as shown in Table I. By default, Orkut is used, since it has the highest vertex degree among the

| Dataset       | Vertex | Edge   | Type   |
|---------------|--------|--------|--------|
| Orkut         | 3.07M  | 117.18M| Social |
| Wiki-topcats  | 1.79M  | 28.51M | Network|
| LiveJournal   | 4.84M  | 68.99M | Social |
| WRN           | 23.9M  | 28.9M  | Road   |
| Twitter       | 41.65M | 1.468B | Social |
| UK-2007-02    | 110.1M | 3.945B | Social |

For testing the scalability, we build a GPU cluster with 6 physical nodes, each of which is equipped with CPU Xeon E5-2698 v4 (2.20GHz, 20 cores) and 2 NVIDIA V100.
GPUs (16GB GPU memory on each GPU). Other experiments are run at a NVIDIA DGX workstation with CPU E5-2698 (2.2GHz, 20 cores), and 4 NVIDIA V100 GPUs. For the middleware accelerator abstraction, we treat CPU in one node as an accelerator which has a 20-thread multithread processing model, and we treat each GPU as an accelerator which has 1024-thread multithread processing model. We build our system with Ubuntu 16.04.5 LTS and deploy a Nvidia-docker framework for simulating the distributed environment with heterogeneous processors. We construct a cross compilation solution by using maven, sbt and cmake to manage and configure the global project dependencies. For Spark runtime, we use Java 8 and Scala 2.11. For local C++ and CUDA programming, g++7 and CUDA 10.0 are used. The source code is available in [GX-Plug repository](http://example.com). Also, code for GraphX integration can be found at [GraphXwithGPU repository](http://example.com), and code for PowerGraph integration can be found at [PowerGraph-GPU repository](http://example.com).

### B. Results

1) **Results on real graphs:** Figure 8 compares the performance of GraphX and PowerGraph with non-accelerator (no prefix), CPU-integrated (prefix CPU+) and GPU-integrated (prefix GPU+) The y-axis is in log scale. In relatively computation-dense applications such as LP and SSSP-BF, acceleration can be observed in total time.

On GraphX, compared with GraphX, GPU+GraphX achieves up to 7x acceleration in SSSP-BF, and up to 20x acceleration in LP algorithm. CPU+GraphX also achieves up to 4x acceleration in SSSP-BF algorithm and up to 5x acceleration in LP algorithm. On PowerGraph, GPU+PowerGraph achieves up to 25x acceleration in SSSP-BF algorithm and up to 15x acceleration in LP algorithm. CPU+PowerGraph also achieves up to 5x acceleration in SSSP-BF algorithm and up to 10x acceleration in LP algorithm. These results verify the effectiveness of the middleware.

The results on the scalability are shown in Figure 9. First, we compare three competitors, PowerGraph+GX-plug, Gunrock [4], and Lux [19], by varying the number of GPUs.
in Figure 9(a-b). Gunrock is a single-node single-GPU graph system, and Lux is a multi-node multi-GPU graph system. In Figure 9(a), the result (Orkut, PageRank) shows that the runtime cost decreases w.r.t. the number of GPUs. Gunrock performs the best on the single-GPU setting, but the multi-GPU setting is not supported. When there are more than 2 GPUs, the performance of PowerGraph+GX-plug is better than Lux, and the lead is growing, showing better scalability w.r.t. the number of GPUs. We proceed to evaluate the scalability on larger datasets, i.e., Twitter and UK-2007, in Figure 9(b). Gunrock gets overflowed on the two datasets, because it only supports the single-GPU setting and the graph data cannot be accommodated by a single GPU. PowerGraph+GX-plug performs better than Lux on the two datasets. For example, PowerGraph+GX-plug is about 40% faster than Lux when processing Twitter with 4 GPUs. The technology pathways of Lux and GX-plug are different. The former focuses on exploiting GPU internal mechanisms, while the latter explores more optimizations on the upper system end, e.g., synchronization skipping, which may become more critical for the scalability on large datasets. There is no result for using 4 GPUs on UK-2007, for all methods, because the system GPU memory capacity is exceeded. Then, we examine the scalability of PowerGraph+GX-plug on different graph algorithms in Figure 9(c). It can be observed that the sublinear speedup in computation is achieved. In particular, the runtime cost of SSSP-BF decreases from 14s to 7s, if the number of GPUs is increased from 2 to 4. The result of mixing and matching different accelerators, i.e., CPUs and GPUs, is shown in Figure 9(d). It shows that the runtime cost decreases if the computation power increases. We will discuss the workload balancing on the heterogeneous system.

2) Effect of Pipeline Shuffle: Figure 10 shows the experiment results of the performance of pipeline shuffle mechanism. We consider 3 competitors, “Pipeline*”, “Pipeline” and “Without pipeline”, in corresponding to the results with optimal blocksize, fixed blocksize, and the one without pipeline parallelism. Experiment shows that “Pipeline*” can achieve 30%-50% acceleration rate compared with “withoutPipeline”. Also, “Pipeline*” can improve pipeline performance as 20%-30%, compared with “Pipeline”.

3) Effect of Synchronization Caching & Skipping: Figure 11(a) shows the performance of the synchronization caching mechanism. We use both synthetic and real graph datasets as input, and use SSSP-BF algorithm for testing the workload. The experiment result shows that we can get 2-3x acceleration in GraphX integrations. For the results on PowerGraph, it is much more efficient than GraphX. We can get up to 150% acceleration in both synthetic and real datasets.

Figure 11(b) shows the performance of synchronization skipping mechanism. We use SSSP-BF algorithm for testing the workload, and count the number of iterations skipped on both synthetic and real datasets. We also compare the result with the number of iterations when synchronization skipping mechanism is disabled. For real datasets, the synchronization skipping mechanism achieves 60%-90% decrease of the number of iterations. However, the effect on synthetic dataset is insignificant, where the data are more uniform, due the random generation of nodes and edges. For real datasets, there tends to be more clusters of dense partitions, leading to better partitioning results that triggers synchronization skipping.

4) Effect of Workload Balancing: Figure 12 shows the results of workload balancing. We compare the difference of system performance with and without workload balancing. Also, we plot the best performance can be achieved in accordance to our estimation model as discussed in Section III-C.

Figure 12(a) shows the scenario in which the hardware configuration of distributed nodes are fixed, and the partitioning strategy can be tuned (Case 1, Section III-C). We construct two distributed nodes for the experiment. One node contains 1 GPU + 1 CPU, and the other contains 3 GPUs + 1 CPU. We evenly partition the graph dataset to all nodes, which is the default setting of distributed graph systems, and is denoted as “Not Balanced”. We compare it to the one with our balancing strategy as discussed in Section III-C, which is denoted as “Balanced”. It shows that the workload balancing can significantly improve the system performance. Also, the balanced result is very close to the theoretically optimal result.

Figure 12(b) shows the scenario in which the partitioned results are fixed, and the hardware configuration can be tuned (Case 2, Section III-C). We construct 2 distributed nodes with the same hardware configuration. We vary the data load of distributed nodes to observe the effect of hardware configuration tuning. Without balancing techniques, both distributed nodes are with 1 GPU, denoted as “Not Balanced”. With balancing techniques, we can estimate the number of GPUs needed in accordance to the data load and dynamically allocate appropriate number GPUs, denoted as “Balanced”. It shows that the workload balancing can significantly improve the system performance. Also, the balanced result is very close to the theoretically optimal result, demonstrating the merits of workload balancing strategies.

5) Effect of Runtime Isolation: We hereby examine the performance of computation daemon on the runtime isolation by designing a comparative test to compare the influence of GPU initialization between daemon-agent based solution and direct GPU call solution. A larger number of iterations corresponds to a higher number of times of CPU-GPU runtime environment switching. Results in Figure 13 (11 iterations) show that our solution significantly reduces unnecessary initialization costs. The benefits would be amplified when the number of iterations is increased.

6) Middleware Scalability: We examine the scalability of our middleware, by varying the number of distributed nodes, in Figure 14. It plots the ratio of time cost taken by the middleware to the cost of the entire system, for different graph tasks on different distributed systems, e.g., PowerGraph and GraphX. It can be observed that, for all graph tasks, the time ratio of the middleware decreases w.r.t. the increase of number of distributed nodes. The downhill trend reflects good scalability of the middleware in a larger scaled distributed computing environment, where the cost can be dominated by
the gradually enlarged synchronization overhead of distributed system side. Also, the time ratios of middleware are mostly between 10% and 20%, especially for algorithms with high operational intensities. Particularly, PageRank takes only about 10% of total cost in a distributed system with 32 nodes. LP is different, since it is a fully iterative algorithm, corresponding to a low operational intensity.

In summary, the low cost ratio and the downhill trend demonstrate good scalability of our middleware.

7) Block Size Selection: To examine the effect of the block size selection, we measure the pipeline performance in different with different amount of blocks $s$, in Figure 15. We also compare the estimated $s_{opt} = \frac{a}{b_{opt}}$ with the real result. For both LP and PageRank algorithms, we use the first iteration as the testing data. For SSSP algorithm, we use 6-th iteration as the testing data, since the computation workload is the maximum during the entire execution. We can find that when $s$ increases, iteration time cost first decreases, and then increases. Thus, for $b = \frac{a}{2}$, when $b$ increases, iteration time cost also tends to first decrease, and then increase.

We also give our estimated $s$ following the analysis here for the 3 different algorithms. It shows that when real $b$ and $s$ are close to the estimated result, the pipeline performance is also close to the estimated one, showing the accuracy of our estimation. Also, the optimal performance can be reached when real $b$ and $s$ are close to our estimation.

VI. RELATED WORKS

Distributed CPU-based Systems. With the prosperity of distributed system, people investigate common operator sets inside diverse graph primitives for scaling out in the distributed environment. As a forerunner, Pregel [11] is proposed by Google on large-scale graph computing, following the BSP model. In BSP, graph computation are divided into iterations and intermediate results can be globally synchronized at barriers called super-steps. GraphLab [32] allows asynchronous computation and dynamic asynchronous scheduling, whose programming model also isolates the user-defined algorithm from data movement. To achieve better workload balancing on natural graphs, PowerGraph [3] uses a more flexible GAS abstraction for power-law graphs.

There are also many embedded graph processing systems built on existing distributed systems to gain the benefits of task scheduling and data management. GraphX [2] is one of the most successful representative built on top of Apache Spark [33]. HaLoop [34] is a similar distributed graph processing system, in particular, extended from Hadoop [35].

However, most works pay little attention to the computation intensiveness of large-scale graph processing. Efforts on scheduling balancing and data accessing also incur extra cost in computation, making the system even slower than single-node solutions. It is thus desired to have a scale-up solution for distributed graph systems.

Single-node Parallel Graph Algorithms. There also exist hardwired graph primitive implementations for the single-node environment. Merrill et al. propose linear parallelization of BFS algorithm on GPU [36]. Soman et al. studies graph algorithms based on two PRAM connected-component [37]. Several parallel Betweenness Centrality implementations are available on GPU based on the work of Brandes et al. [38]. Davidson et al. [39] propose a work-efficient Single-Source Shortest Path algorithm on GPU.

Low-level graph parallel solutions can have best performance only on specific computation tasks, but are not general for diversified graph applications. Also, the hardwired primitives are challenging to even skilled algorithm engineers, making such solutions hard for being deployed in real systems and applications.

High-level GPU Programming Model. There are also existing works on high-level graph operations for GPU. Zhong and He devise Medusa [40] on a high-level GPU-based system for parallel graph processing using a message-passing model, which is arguably the earliest work for GPGPU development for graphs. CuSha [41], targeting a GAS abstraction, avoids non-coalesced memory accessing and avoids irregular memory accessing. Gunrock [4] implements a novel data-centric abstraction centered on operations on a vertex or edge frontier rather than designing an abstraction for computation. Recently, there are a few works on GPU graph processing system built on distributed systems, among which Lux [19] is one of the representatives. Users can use GPUs in multiple physical nodes for efficient computation. However, without the support of mature distributed systems, Lux faces a series of challenges, such as robust distributed data management, scheduling balancing, effective fault recovery, and efficient data synchronization with physical layers, and thus falls short in addressing technical issues arise in large-scale graph data management and analytics.

VII. CONCLUSION

In this paper, we propose a middleware for the integration of heterogeneous distributed graph systems and accelerators. Our middleware is versatile in the sense that it supports different programming models, computation models, and runtime environments. For reinforcing the middleware performance, we devise a series of techniques, such as pipeline shuffle, synchronization caching and skipping, partitioning, and parameter configuration for intra-, inter, and beyond iteration optimization. Extensive experiments show that our middleware achieves good performance in large-scale graph processing.

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