Heterogeneous adaptive heuristics for graph processing in Geo distributed Data Centre

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Abstract: Graph processing is an emerging computation model for a wide range of applications and graph partitioning is important for optimizing the cost and performance of graph processing jobs. In this paper, we propose a heterogeneous adaptive heuristics for geo-aware graph partitioning method which aims at minimizing the inter Data centre cost on data transfer time of graph processing jobs in geo-distributed DCs while satisfying the WAN usage budget. Heuristics can be multiple pass for graph processing. It is effective on assigning edges to different nodes. It adopts adaptive heuristics which address the challenges in WAN usage and network heterogeneities separately. Heuristics can be also applied to partition dynamic graphs minimize lightweight runtime overhead. Evaluation results show that proposed technique can reduce the inter-DC data transfer time by up to 78% and reduce the WAN usage by up to 80% compared to state-of-the-art graph partitioning methods with a low runtime overhead.

Keywords*:* Graph Partitioning, Adaptive Heuristics, Wide Area Network, Geo-distributed Data centers.

1. Introduction

Graph processing is an emerging computation model for a wide range of applications, such as social network analysis (Ching et al, 2015; Elyasi, 2019), natural language processing (Gonzalez et al, 2015) and web information retrieval (Low, et al, 2012). Graph partitioning plays a vital role in reducing the data communication cost and ensuring load balance of graph processing jobs. Many graph applications, such as social networks, involve large sets of data spread in multiple geographically distributed (geo-distributed) datacenters (DCs). For example, Facebook receives terabytes of text, image and video data everyday from users around the world (Ugander, 2015). In order to provide reliable and low-latency services to the users, Facebook has built four geo-distributed DCs to maintain and manage those data. Also, it is sometimes impossible to move data out of their DC due to privacy and government regulation reasons. It is inevitable to process those data in a geo-distributed way. We identify a number of technical challenges for partitioning and processing graph data across geo-distributed DCs. First, the data communication between graph partitions in the geo-distributed DCs goes through the Wide Area Network (WAN), which is usually much more expensive than intraDC data communication.

Most existing cloud providers, such as Amazon EC2, charge higher prices on inter-region network traffic than on intra-region network traffic (Malewicz et al, 2010). Traditional graph partitioning methods which try to balance the workload among different partitions while reducing the vertex replication rate (Minkov, et al, 2006) may end up with large inter-DC data transfer size and hence large WAN cost. Another extreme example is to replicate the entire graph data in every DC in advance, which although greatly reduces the inter-DC data transfer size during graph processing, causes huge WAN cost for data replications. Hence, a more efficient approach to reduce the WAN usage cost during graph partitioning in geodistributed DCs is needed.

Second, the geo-distributed DCs have highly heterogeneous network bandwidths on multiple levels. On the one hand, the uplink and downlink bandwidths of a DC can be highly heterogeneous due to the different link capacities and resource sharing among multiple applications. On the other hand, the network bandwidths of the same type of link in different DCs can also be heterogeneous due to different hardwares and workload patterns in the DCs. For example, it has been observed that the network bandwidth of the EU region is both faster and more stable than the network bandwidth of the US region in Amazon EC2.

Thus, even if the amount of data transfered across DCs is minimized, it can still result in long inter-DC data transfer time if not considering the multiple levels of network heterogeneities. To address the above challenges, we propose a geo-aware graph partitioning method named heterogeneous adaptive heuristics for geo-aware graph partitioning method which aims at minimizing the inter Data centre cost on data transfer time of graph processing jobs in geo-distributed DCs while satisfying the WAN usage budget. Compared to other resources such as CPU and memory, WAN bandwidth is more scarce in the geo-distributed environment.

Thus, our goal in this paper is to optimize the performance of graph processing jobs by minimizing the interDC data transfer time while satisfying user-defined WAN usage. budget constraint. However, considering the heterogeneities in graph traffic and network bandwidths, and given the large sizes of many geo-distributed graphs, obtaining a good partitioning result is non-trivial. It adopts optimization phases which address the two challenges in WAN usage and network heterogeneities separately. Initially, we propose a streaming heuristic which aims at minimizing the inter-DC data transfer size (i.e., runtime WAN usage) and utilize the one-pass streaming

partitioning method to quickly assign the edges onto different DCs. Secondly propose two partition refinement heuristics which identify the network performance bottlenecks and refine the graph partitioning generated in the first phase to reduce the interDC data transfer time.

The following of this paper is organized as follows. Section II introduces the background and related work. We formulate the graph partitioning problem in Section III and introduce our proposed techniques in Section IV. We evaluate heterogeneous adaptive heuristics in Section V and conclude this paper in Section VI.

2. Background & Related work

In this section, we provide background information about the graph execution model. Graphs in production are typically too large to be efficiently processed by a single machine. Distributed graph analytics frameworks are thus developed to run graph analytics in parallel on multiple nodes in data centres. Before running the actual analytics, the input graph is divided into several partitions. Figure 1 represents the graph partitioning model
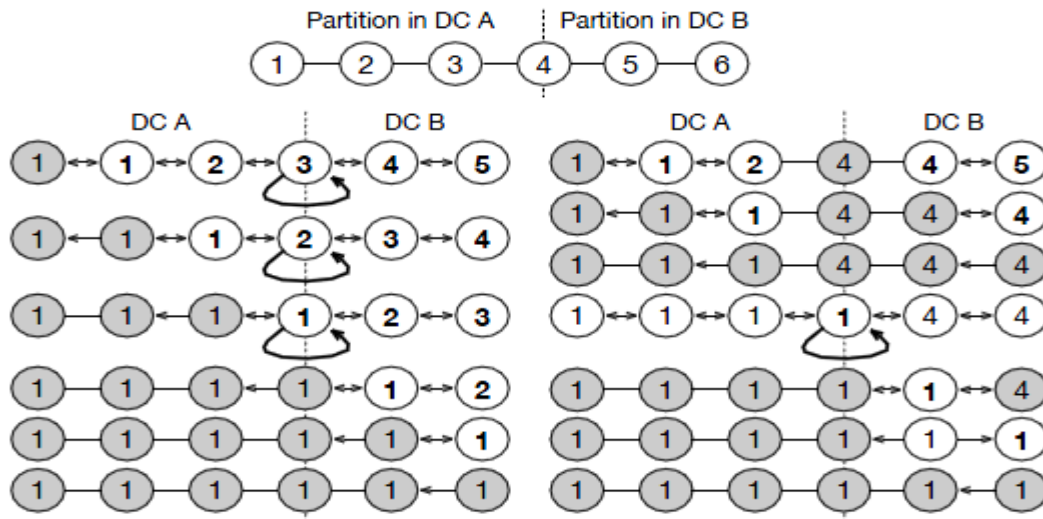

Figure 1: Graph Partitioning model under DC using Connected Component of Data centres

The frameworks will then handle the synchronization and necessary message passing among data centres. Most of the state-of-the-art solutions (̦et al, 2006) provide a vertex-centric abstraction for developers to work on similar to Google's Pregel and implement the Bulk Synchronous Parallel (BSP) model for inter-node synchronization (Po et al, 2015). Such an integration of programming abstraction and synchronization model allows developers to "think like a vertex," making the development of graph analytics applications intuitive and easy to debug.

3. Graph Partitioning problem

In this section, we define problem of graph Partitioning method ascritical design importance to design efficient mechanisms to run graph analytics applications in a geographically distributed manner across multiple datacenters in a paradigm called widearea graph analytics. In particular, the fundamental challenge is to process the graph with raw input data stored and computing resources distributed in globally operated datacenters, which are inter-connected by wide-area network[10]. Unfortunately, existing distributed graph analytics frameworks are not sufficiently competent to address challenges

Heterogeneous Task and Resources in Data center leads to proper graph bisection.

Time complexity in partitioning dynamic graphs with different data sizes

Power law distribution leads to high traffic in some set of nodes leaving other nodes without any weight

Selecting optimal portioning is NP – Complete on employing breadth first search

4. Proposed Technique

In this section, we model a heterogeneous adaptive heuristic to model a graph partitioning for cost aware data centres. Initially task to be Processing towards execution on geo-distributed data centres has been represented in form of graph is as follows

Given a graph G = (N, E, WN, WE)

N = nodes (or vertices)

E = edges

WN = node weights

WE = edge weights

N can be thought of as tasks, WN are the task costs, edge (j,k) in E means task j sends WE(j,k) words to task k.

Given the initial locations of vertices (i.e., where the input data of vertices are located), we adopt the streaming graph partitioning approach to quickly partition a graph. We will first explain the high-level principle of its design and the general idea behind its correctness guarantee. The following algorithm explains the process of the data centre handling using heuristics.

Algorithm 1: Adaptive Heuristics

Set execution mode to global, global update counter k ← 0, current error δ ←∞;

    while δ> ∞ do

        if (Execution mode is global) then

            Perform a global update: x(k+1) F(x(k));

δ k+1 ←D(x(k+1);x(k));

if (δ k+1 <δ k) then

        Switch execution mode to local;

        else

δ k+1 ←δ k;

k ←k + 1;

        else

      Apply local updates in each datacenter concurrently (as in Procedure 2), until any datacenter calls forceModeSwitch() or all datacenters call voteModeSwitch().

        Switch execution mode to global;

    return x(k).

5. Simulation Results

In this section, the proposed model is to partition the data centre into cluster on various workloads on specific environment. The environment is configured with high frequency and large RAM capable specification as simulation model. The workload is overestimated; the resource clustering basis of the application exceeds the actual demand on overhead and job execution time computation. The small jobs with deadlines execute earlier than the next control interval of the job on the resource clusters.

The latency model to estimate the latency of each input job or task, on calculating the sum of the delay expectations of the jobs on the longest path in each time window has been computed easily. The latency of the stream data on the path is equal to the product of the delay of the maximum latency operation on the path and the path length in the queued processing on reinforcement learning based online parameters of the heuristics.
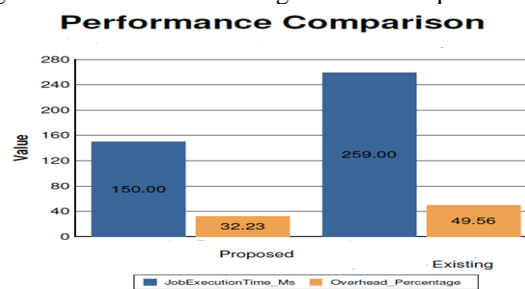

Figure 2: Performance outcome of the proposed model against existing model

The data centre consisting of multiple Computation task is updated with respect to quality of service and cost has been adapted using heuristics. In this reconfigurations (stability) are achieved on resource scheduling strategy distributed environments to control the average latency. The Probability can be cluster to fluctuate significantly over time.

The evaluation of the model is carried out on estimating the performance of the partitioning algorithm and the resource adjustment algorithm on various workloads. The figure 2 provides the performance results and performance values has been illustrated in the table 1.

Table 1: Performance Computation of the graph partitioning model

Technique	Job execution Time in ms	Overhead in percentage
Proposed	150ms	32.23
Existing	259ms	49.56

From the above results it is clear that latency violations are less under the dynamic workload. In this assumption is made that there is resource expansion adjustment on the resource adjustment calculation using adaptive heuristics. The partition can fluctuate significantly over time which is suitable for the arbitrary probability distribution of the interracial time and processing time of the job on application of dynamic varying workloads.

6. Conclusion

In this paper, we propose a geo-aware graph partitioning method named heterogeneous adaptive heuristics to minimize the inter-DC data transfer time of graph processing jobs in geo-distributed DCs while satisfying the WAN usage budget. Proposed model incorporates two optimization phases. While the first phase utilizes the onepass streaming graph partitioning method to reduce inter-DC data traffic size when assigning edges to different DCs, the second phase identifies network bottlenecks and refines graph partitioning accordingly. The experiment results on both real geo-distributed DCs and with simulations have demonstrated that proposed is effective in reducing the inter-DC data transfer time with a low runtime overhead. As future work, we plan to extend our techniques to other graph processing models, experiment on graphs with larger sizes and heterogeneous computing environments with GPUs

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