Bi-objective Traffic Optimization in Geo-distributed Data Flows

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ARTICLE INFO

Article history: 
Received 12 July 2018 
Received in revised form 13 March 2019 
Accepted 17 April 2019 
Available online 25 April 2019

Keywords: 
Distributed flow optimization 
Latency minimization 
Communication minimization 
Iridium

ABSTRACT

Recently, there have been several proposals in the area of geo-distributed big data processing. In this work, we aim to address a limitation of the existing solutions, namely to optimize task allocation across geographically distributed data centers, in a way that both the total traffic and the running time of the whole processing in complex multi-stage flows are targeted. Apart from proposing concrete efficient solutions for this combinatorial problem, we advocate to take a critical stand on the broadly spread claim that transferring distributed data to a single or fewer places is too costly. In our proposal, we judiciously reduce the participation of some data centers in the flow execution, and we show that, in a wide range of settings, this yields significant benefits. We show that a stochastic solution is superior to a fast greedy one, at the expense of optimization time of up to a few minutes. Compared to a state-of-the-art solution, we manage to decrease total traffic by 44% and running time by 37% on average. In several cases, the improvements can reach 1-2 orders of magnitude. Moreover, we provide evidence that simple heuristics are inferior. Our experimental evaluation comprises both extensive simulations and real runs in Spark.

1. Introduction

Data-intensive processing platforms is still a technology in evolution. The emergence of the MapReduce framework and its descendants, such as Spark and Flink, has shaped the way in which big data is nowadays processed and analyzed. However, these technologies are tailored to a single data center, since they implicitly assume either a powerful multi-core server or a shared-nothing cluster, where the communication between the nodes is very fast. At the same time, the need for analyzing data from geo-distributed locations is rapidly increasing in several domains, which gives rise to the need to adjust and extend the big data processing technologies in order to become applicable across geo-distributed data centers in an efficient manner.

In the recent years, there have been several proposals that aim to address the problem of transferring MapReduce-like solutions to a geo-distributed setting, but they suffer from several limitations. According to a recent survey in [1], a significant such limitation is the lack of solutions that aim to optimize both the total traffic and the flow completion time in a combined manner. For example, there exist proposals that minimize the completion time, e.g., [2], or the total traffic, e.g., [3], but not both. Our work aims to fill this gap.

More specifically, in this paper we focus on the bi-objective traffic optimization problem in data flows, where we aim to reduce the total traffic of the network while keeping the running time under a given threshold set by the user (explained in Section 4.1). We use directed acyclic graphs (DAGs) to represent data flows. Each node represents a job (for example, in Spark each node refers to a Spark Stage) that needs to be parallel executed on different data centers (DCs) while the edges of the graph represent the data movement between the jobs. For example, Fig. 1 shows a DAG in Spark where each node is a stage and the edge between the stages represents the data movement that occurs due to the groupBy transformation. Such data movements incur traffic cost and may contribute to the total running time. The goal is, given an arbitrary initial distribution of the data, to distribute the workload among the DCs for each job, so that both objectives are met. A naive solution is clearly exponential in the number of the jobs.

The main characteristics of our approach are twofold. On the one hand, we exploit existing solutions to the largest possible extent. We use the state-of-the-art Iridium solution in [2] for minimizing running time and we extend it in two ways: (i) to make it more efficient for multi-job DAGs instead of simple two-stage MapReduce ones and (ii) to account for total traffic as well. On the other hand, we challenge the validity of a main motivation behind geo-distributed data flows, namely that it is too costly to gather data in a single place, e.g., [1,4,5]. We develop a fast Greedy solution and a more efficient but slower stochastic process that both

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aim to investigate task allocations that either decrease or discard the participation of some DCs to some jobs.

In summary, we make the following four contributions, whereas we also implemented our solution in Spark:

1. We show that using less DCs is more beneficial than using all the DCs available in a wide range of cases; the benefits are both in total traffic and flow execution time.
2. We propose two algorithms, a greedy and a stochastic one, that decrease the total traffic by re-arranging the task placement between the DCs, staying always under a given threshold in running time.
3. We conduct thorough experiments using realistic parameters. We show that our stochastic solution achieves an average of 37% reduction in the total running time while reducing traffic by 44% on average compared to the proposal in [2]. The improvements are higher if a hybrid initialization scheme is followed. In some cases, the improvement margins are 1-2 orders of magnitude. This is at the expense of optimization times of up to a few minutes.
4. We show that, similarly to using all available DCs, naive solutions, such as using a single DC for all job executions, are inferior to our techniques that more judiciously restrict the participation of all DCs in the flow execution.

The remainder of the paper is outlined as follows. In Section 2, we provide two motivation examples to show the challenges in our bi-objective optimization problem and the benefits from using less DCs. The related work is discussed in Section 3. Our proposal and our algorithms are described in Section 4. In Section 5, we present our experiments and their results. Finally, in Section 6, we make a final discussion.

2. Motivation example

Assume that we have a simple two stage graph running on two DCs, DC1 and DC2. That means that each stage of the graph is executed on both DCs in parallel. The overall size of data is 30 MB. Initially, the data of the first stage are divided to the DCs as follows: 10 MB on DC1, and 20 MB on DC2. The uplink and downlink of DC1 (resp. DC2) are 5 MB/s and 10 MB/s (resp. 10 MB/s and 10 MB/s). The first allocation equally splits the workload for the second stage. This means that DC1 has to upload 5 MB and DC2 has to upload 10 MB. Also, DC1 downloads 10 MBs and DC2 downloads 5 MB. Since data transmissions run in parallel, the running time is determined by the slowest link. As such, the total running time is 1 s and the total traffic is 15 MB, as can be seen in Fig. 2a. However, there is a better configuration, in which the first DC has to upload 7.5 MB and the second 5 MB only; this is achieved by allocating 25% of tasks of the second stage on DC1 and 75% on DC2. This results in total running time of 1.5 s and total movement of 12.5 MB. This means that, in general, traffic time and running time can be contradicting objectives, thus it requires particular attention when trying to optimize both.

Now let’s consider a more complex case, where 4 DCs participate (the key parameters are shown in Table 1). If we assign an equal fraction of tasks in each DC, then each DC has to upload and download some data. The time for these moves depends on the DC’s uplink and downlink speed. The total running time of the job is the maximum of all the link finish times, as previously. In our example, the total running time is 46.25 s and the total amount of data moved is 168.75 MB. This time is due to the bottleneck DC, DC3, the downlink speed of which is 1 MB/s and the amount of data it has to download is 0.25 × 185 = 46.25 MB. If we assign the task allocation to Iridium [2], the new allocations are 0%, 78.5%, 0%, and 21.5%, respectively. This means that DC1 and DC3 do not execute any tasks at the second flow stage and therefore, they do not download any data; however, they need to distribute their data to the other DCs that have non-zero allocation. This scheme reduces time to only 12.95 s and data movement to 161.78 MB. This example shows that it is possible to improve regarding both the running time and the total data movement by not using all DCs throughout the execution.
Our work can be seen as an extension to Iridium. In our extensions, both objectives are targeted more systematically and efficiently, whereas we also target more complex flows, i.e., flows with multiple stages. As shown in Section 5, our techniques are more efficient than Iridium in both metrics. We continue the discussion of the related work in the next section.

3. Related work

An extensive survey of geo-distributed extensions to MapReduce has appeared in [1]. The most relevant research to our work consists of proposals that target either the total traffic or the flow running time, summarized in Table 2.

Regarding the works that target the total traffic, a prominent example is the WANalytics proposal in [3]. Similar to our work, it targets generic DAGs but does not consider running time. [6] focuses also on data traffic and suggests a Spark-based framework that targets the best placement of data, but does not set an upper threshold on running time. Pixida [4] converts the data traffic reduction problem to a graph repartitioning one. G-MR [7] is a Hadoop-based framework that detects the best task placement through solving a shortest path problem considering either running time or data movement, but not both; moreover its complexity is exponential in the number of nodes. There are also some more specific solutions. For example, Meta-MapReduce [8] focuses on decreasing the data movement by avoiding to move data that will not participate in the final output. Jetstream [9] decreases the data traffic using degradation, aggregation and filtering operations on the data at the expense of lower accuracy. Geode [5] targets both data traffic and running time reduction in SQL queries using caching and copies of the data, but the proposed technique cannot be extended to generic DAGs.

Regarding the proposals that target running time, we have already introduced Iridium [2], against which we directly compare our proposal. Iridium has been compared against [3], and is found that it achieves much lower times at the expense of small increases in total traffic; on the contrary, we show that we can improve both metrics. However, Iridium also deals with the problem of initial data placement, whereas we assume that this placement is fixed. Nebula [10] tries to find the optimal task allocation to minimize the running time but does not consider the overall data traffic. Rout [7] also tries to minimize the running time by selecting the most beneficial data placement but does not focus on data traffic either. G-Cut [11] aims to minimize the running time by rearranging the tasks while keeping the traffic below a threshold, but it is specific to geo-distributed graph processing. The proposal in [12] targets both metrics but is tailored to a single MapReduce flow with the reducer being executed on a single DC.

Note that there are several proposals in geo-distributed processing that focus on other issues than performance; for example, [13] focuses on resilience, and [14] deals with DC configuration. Other topics that are tangential to our research involve understanding of wide-area data transfer performance, e.g., [15], flow modeling and performance prediction, e.g., [16], access to geo-distributed Web Services, e.g., [17], and advances in edge computing, e.g., [18].

Finally, our stochastic solution has been inspired by a randomized solution for determining the appropriate degree of parallelism in Spark flows, where it was proven that such stochastic solutions are a powerful tool for finding local optimal solutions in bi-objective problems [19]. Here, we capitalize on this experience and we successfully apply a stochastic solution to a new setting.

4. Our proposal

Our proposal aims to tackle the two main limitations of existing works: (i) it considers generic DAG flows in a more comprehensive and efficient manner through taking into consideration the impact of the decisions taken regarding a specific stage of the flow on the other ones; and (ii) it aims to decrease both the overall running time and the total communication across inter-DC connections. The rationale behind the design of the techniques is that, in several scenarios, it is more beneficial to allocate (the largest part of) the workload to less DCs than those initially holding the data.

We make three salient assumptions: (i) as in [2], the inter-DC communication cost is the dominant one; (ii) a limited number of DCs is adequate to perform the main processing corresponding to a DAG vertex; and (iii) the initial distribution of input data across DCs is fixed.

4.1. Notation and problem definition

A geo-distributed data flow is represented as a DAG $G(V, E)$. Each node $v_j \in V$, where $j = 1 \ldots N$ and $N = |V|$, represents a job and each edge represents a shuffle data movement between the jobs. For example, in Spark data flows, a job corresponds to a Spark stage; in between such stages, data shuffling takes place. Each job runs in parallel in $M$ DCs: i.e., each DC becomes responsible for a fraction of the job execution with the magnitude of the fraction devised by our algorithms. Conceptually, the workload of a job is split into small units of work, each allocated to a specific processing element, e.g., a multi-core server of a specific DC, as an atomic unit. We refer to these splits as tasks. Due to shuffling, in the generic case, it is necessary to move data between DCs before the execution of each task. This data movement is the dominant factor regarding the running time of the jobs, while the actual execution time of the job is considered to be negligible.

In this work we deal with the allocation of sets of tasks to each DC for each job. Let $l^j$ be the input dataset size of $v_j$. If the selectivity of the job is $a^j$, then the output dataset is of size $S^j = a^j \cdot l^j$. If $v_j$ has outgoing edges in $G$, $S^j$ is divided into $M$ parts to be sent to the jobs downstream, denoted by $r^l_j S^j$, $l = 1 \ldots M$, s.t. $\sum r^l_j = 1$. Essentially, $r^l_j$ corresponds to the fraction of tasks of the children nodes of $v_j$ assigned to the $l$th DC (tasks are assumed to be infinitesimally divisible). In other words, $r^l_j$ values affect the workload allocation of jobs $v_k$, where $(j, k) \in E$. Overall, each DC has to transfer a fraction of $(1 - r^l_j)$ of its local output data $S^j_l$, and to receive a total of $r^l_j \times (S^j_l - S^j_l)$ data from all the other DCs. Following the rationale in [2], we specify the uplink (resp. downlink)

\begin{table}[h]
\centering
\caption{Summary of the most relevant related work. (*) Not both metrics simultaneously; (**) tailored to SQL queries; (***) tailored to graph processing.}
\begin{tabular}{|l|c|c|}
\hline
Proposal & Aggregate traffic reduction & Running time reduction \\
\hline
WANalytics [3] & ✓ & \\
Shuffle Optimization [6] & ✓ & \\
Meta-MapReduce [8] & ✓ & ✓(*)
Jetstream [9] & ✓ & \\
Geode [5] & ✓(**) & ✓(**)
Iridium [2] & ✓ & \\
Nebula [10] & ✓ & \\
Rout [7] & ✓ & \\
THIS WORK & ✓ & ✓
\hline
\end{tabular}
\end{table}
bandwidth of the $i$th DC as $U_i$ (resp. $D_i$). Table 3 summarizes the main notation.

Based on the above, the time for a site to send data regarding the output of a job is $TU_j = (1 - r_j^i) * S_j^i / U_i$, and the time to receive data is $TD_j = r_j^i * (S_j^i - S_j^o) / D_i$. The running time $RT_j$ of

$$
\text{The total data movement from a node } v_j \text{ is equal to } \sum_{i=1}^M r_j^i * S_j^i. \text{ The total data movement is } DM(G) = \sum_{j=1}^N \sum_{i=1}^M r_j^i, \text{ where } v_j \text{ has at least one outgoing edge.}
$$

The running time of a $G$, $RT(G)$ is the maximum sum of $RT_j$ values across any path from a source job ($v_j$ without incoming edges) to a sink one ($v_j$ without outgoing edges); sink nodes have zero running time by default.

In this paper we aim to the bi-objective traffic optimization of the data flow. That means that we try to minimize the total data movement considering the execution time of $G$. At a nutshell, we follow a two-step approach:

1. We use Iridium [2] as our guideline for the initial assignment of tasks, i.e., computation of the $r_j^i$ values, to the DCs. Iridium decides the allocation for each job separately, after performing a topological sorting on $G$ and considers the nodes from the upstream to the downstream ones.

2. We re-arrange the allocations with a view to decreasing the total movement cost while not allowing running time degradation more than $\varepsilon$.

More formally, the problem we target is defined as follows:

**Problem statement:** Given a dataflow $G$, a fixed distribution of the initial data across Ms DCs, and a running time value $RTbase$, compute the $r_j^i$ values s.t. $DM(G)$ is minimized and $RT(G)$ is always less than $(1 + \varepsilon)RTbase$, where $\varepsilon$ is a small constant $\varepsilon > -1$. If $0 > \varepsilon > -1$, then we enforce the solutions to seek improvements regarding both $DM(G)$ and $RT(G)$; when $\varepsilon$ is positive, we tolerate increases in $RT(G)$.²

Note that the higher we set $\varepsilon$, the more the problem tends to be a single-objective optimization (that of minimizing $DM(G)$) in practice.

In our solution, the first step derives the $RTbase$ value from the result of the Iridium solution. Then, our main contribution refers to the second step, for which we propose two techniques, a stochastic and a greedy one.

4.2. A greedy solution

The first solution is a greedy algorithm that is described in Algorithm 1. The input of the algorithm is (i) the initial allocation of tasks on the DCs according to [2], (ii) the threshold $RTthreshold = (1 + \varepsilon)RTbase$, where $RTbase$ is the initial $RT(G)$, and (iii) the initial $DM(G)$. The output is the new allocation of tasks optimized for lower $DM(G)$ with the new $RT(G)$ to be less than the threshold.

Algorithm 1 consists of two loops. The internal one iterates over all jobs. Its rationale is that the DC with the smallest non-zero $r_j^i$ acts as a bottleneck, and its fractions of tasks should be further decreased by an $\beta$ factor (by default set to 1/3). So the algorithm detects the bottleneck DC for each job, decreases its $r_j^i$ by $\beta$, and distributes the removed workload to all the remaining DCs proportionally to their own current portions (inactive DCs remain with zero allocation). After we exit the internal loop, we choose the most beneficial modification of the task allocation referring to a single job in terms of $DM(G)$ whose $RT(G)$ is under the threshold. This reallocation triggers reallocations to all the other nodes downstream, since the data of the downstream nodes are re-divided ($S_j^i$ is re-arranged to the DCs); the reallocation is computed through a LP solution as in [2]. This process is repeated $N * M$ times.³

The complexity of the technique loop is dominated by solving the linear program with $M$ variables of [2] for all the affected jobs, which are $O(N)$. Therefore, the total complexity is solving an LP program $O(N^2 M)$ times. The number of reallocations considered is also in $O(N^2 M)$.

4.2.1. Example

Assume that we have a linear DAG $G$ with three nodes running on three DCs as can be seen in Fig. 3; each node is being executed in all the DCs in parallel. In the figure, each circle corresponds to a job-DC pair annotated by the corresponding $r_j^i$ value. The uplink and downlink of the DCs are $U = (10, 1, 10)$,
$D = (10, 5, 5)$. The $S_i^1$ values are $S_i^1 = (120, 100, 50)$ and $\alpha = 1$ for both jobs. Fig. 3a shows the result of Iridium, which decides the allocation of $r_i^1 = (0, 0.75, 0.25)$ regarding the results of the first job. Consequently, $S_i^1$ becomes $(0, 202.5, 67.5)$. Iridium then assigns the fractions $r_i^1 = (0.06, 0.94, 0)$ thus, $RT(G) = 38.19$ s and $DM(G) = 262.15$ MB (Fig. 3a).

Now, let us suppose that we set $RT_{threshold} = (1 + 0.1)38.19 = 42$ s and we execute the external loop of Algorithm 1 a single time. First, we check the first job, for which the 3rd DC forms a bottleneck. We remove 1/3 of its workload and we transfer it to the 2nd DC, which is the only other DC with non-zero allocation; this results in $r_i^1 = (0, 0.83, 0.17)$. The new $RT(G)$ is 40.91 s. The benefit in the data movement is 4 MB (Fig. 3b). Then, Greedy proceeds to the second job and reallocates its tasks as follows: $r_i^1 = (0.04, 0.96, 0)$ (the bottleneck DC is the first one) and the metrics become $RT(G) = 38.46$ s and $DM(G) = 258.1$ MB. The new running time is under the threshold and the benefit for this second re-assignment is 4.05 MB (Fig. 3c). As a final result of this iteration, the most beneficial reallocation is the second one and it is accepted; if it had any downstream nodes, we would rerun LP for these nodes.

Overall, in a single iteration, even in a very simple graph, we managed to improve upon Iridium by 1.5% in terms of $DM(G)$ at the expense of 0.7% increase in $RT(G)$.

4.3. A stochastic solution

Our stochastic solution is an Iterated Local Search (ILS) algorithm that uses Stochastic Hill Climbing (SHC) as an internal heuristic mechanism. The algorithm is described in Algorithm 2. The input of the algorithm is the initial allocation of tasks on the DCs and the threshold on the $RT(G)$. The output is the new allocation of tasks optimized for lower $DM(G)$ as well as the new $RT(G)$ and $DM(G)$. ILS first applies the heuristic mechanism on the initial solution and then iterates $iter1$ times. In each iteration, it creates a perturbation of the current solution, applies the heuristic mechanism to it and checks if the $DM(G)$ is optimized while $RT(G)$ is under the threshold. The rationale behind using hill climbing is not to move very far away from a neighborhood that is considered to be a good starting point, while we perturb the intermediate solutions to adequately cover the search space.

The perturbation is an algorithm that given the initial allocation and a parameter $d$, chooses $d$ random jobs and some random DCs and rearranges their task placement fractions by $\beta$ regardless of the resulting $RT(G)$ and $DM(G)$ values. The Stochastic Hill Climbing heuristic is presented in Algorithm 3. The input of the algorithm is an initial allocation of tasks on the DCs, the threshold of the $RT(G)$, the running time of the initial allocation $RT(G)$ and the initial allocation’s $DM(G)$. It consists of a loop that iterates $iter2$ times. In each iteration, it picks a random job and some random DCs. For each DC, it removes a $\beta$ fraction of its tasks, while dividing this workload to all the other active DCs. If this move is beneficial and the $RT(G)$ remains under the thresh-
Algorithm 3 The SHC algorithm.

Require: allocations, RT threshold, RT(G), DM(G)

for i ← 1 to iter 2 do
  Pick a random job
  for eachDC do
    With probability 0.5, reallocate tasks regarding the random job through reducing DC’s fraction by β
    tempAllocations ← apply changes to G
    Calculate RT(G′) using tempAllocations
    Calculate DM(G′) using tempAllocations
    if RT(G′) ≤ RT threshold then
      benefit ← DM(G) − DM(G′)
      if benefit > 0 then
        allocations ← tempAllocations
        DM(G) ← DM(G′)
      end if
    end if
  end for
end for

return allocations

4.3.1. Example

Continuing on our previous example of Greedy, we now show a possible way in which ILS can behave (Fig. 4a). We assume iter1 = iter2 = d = 1. At first ILS applies SHC on the initial solution. SHC chooses randomly a job, for example the second and then chooses a random DC, for example the second one. The new fractions become \( r_2^2 = (0.37, 0.63, 0) \). The new metrics are \( RT(G) = 100.42 \) s and \( DM(G) = 325 \) (Fig. 4b). The running time is not under the threshold so the new allocation is rejected. Then ILS perturbs the initial solution. It chooses a random job, for example the first and its third DC. The new results can be seen in Fig. 4c. The next move is to call SHC on that new allocation. SHC randomly chooses the second job and the third DC that is \( r_1^2 = (0, 0.97, 0.03) \). The new \( RT(G) \) decreases to 37.79 s and the \( DM(G) \) to 239.42 MB (Fig. 4d). Thus, the solution is accepted. In this example, we can see that ILS can also decrease both \( DM(G) \) and \( RT(G) \).
generated in the range [100 MB, 1 GB]. The $U_i$ and $D_i$ of each DC fall into the range of [100 MB, 2 GB]. The selectivities $\alpha$ of the jobs are between 0.01 and 2 with 50% of the job selectivities ranging from 0.01 to 0.5, 25% of them ranging from 0.5 to 1 and the rest 25% ranging from 1 to 2 (similar to the selectivities in Facebook production analytics according to [2]). For each combination of DAG type, $M$ and $\varepsilon$, we created 60 random instances according to the parameters above, and we report the average values.

Fig. 5. DAGs considered in the experiments (taken from [19]).

Fig. 6. Two representative TPC-H DAGs running in Spark and their corresponding higher-level representation.

5.2. Experimental results and key remarks

5.2.1. Main comparison

In the first set of experiments, we compared Greedy to ILS regarding their improvements upon the technique in [2], when we set $\varepsilon = 0.2$. The results are presented in Fig. 7 and Fig. 8 for $DM(G)$ and $RT(G)$, respectively. As we can observe from Fig. 7, ILS is more beneficial than Greedy regarding the total $DM(G)$. Greedy reduces data traffic by a mean of 1.24% while ILS by 44%. More importantly, ILS reduces, most of the time, the $RT(G)$ as well, with a mean reduction of 37% while Greedy increases the $RT(G)$ by 4%. Especially, for the (E) type of DAG, the reductions are over 90%, which corresponds to improvements by an order of magnitude. In general, the more complex types (C), (D) and (E) benefit more than the simpler ones; this is because, in complex DAGs, there are more inter-dependencies between the DAG nodes that prevent simple greedy heuristics to perform efficiently.

5.2.2. Sensitivity to the $\beta$ and $d$ parameters

In the next experiment, we test the impact of $\beta$, and more specifically, we experiment with decrease factors of 1/2, 1/3, 1/4 and 1/5. We show results for the Large-E and Small-A DAG types in the Figs. 9 and 10. From these figures, we can see that the higher the $\beta$ the more the reduction of the data traffic and running time. More specifically, for Large-E, the average data traffic reductions are 96%, 91%, 81%, 75% and the time reductions 95%, 89%, 70%, 63% when $\beta$ is 1/2, 1/3, 1/4, 1/5, respectively. Additionally, the reduction is significant higher in Large-E than in Small-A. When running the experiments for Small-A, the data traffic reductions are 37%, 32%, 30%, 28% and the time reductions 29%, 24%, 21%, 18%, for the same $\beta$ values.

In the next set of experiments, we examine the impact of the variable $d$ on ILS. More specifically, we run ILS for $d = 2, 3, 4$. The results in Fig. 11 indicate that none value of $d$ outperforms the
others, i.e., ILS does not rely on the value of $d$. However, a pattern for the complex DAGs of type (E) is that for limited or many machine choices (i.e., $M = 5$ and 15, respectively), not allowing too much deviation from the initial solutions through a smaller value of $d$ yields better results; for the $M$ values in between the opposite holds.

5.2.3. Impact of initial allocation and convergence

In this experiment, we tested if setting the Greedy algorithm’s solution as the initial solution in ILS would have better results than initializing according to the Iridium’s solution. We also examined the case in which ILS runs over a random initial allocation. The experiment was performed on the Small-A and Large-E DAGs. The results in Fig. 12 show that, in most cases, the random initialization results to a worse outcome than Iridium and Greedy. Interestingly, Iridium and Greedy not only do not dominate each other, but, in certain cases, are superior by a large margin.

Following up on investigating the issue of initial allocation, we examined the convergence rate of ILS with the three different initializations. The results shown in Fig. 13 indicate that ILS closely approaches its final output well before the 75th iteration, which is the last one. This allows us to propose a meta-solution, in which ILS runs half of its external iterations starting from the Iridium solution and the other half starting according to the Greedy solution. As shown, in Fig. 13, this will not lead to significant performance degradation compared to the results in Figs. 7 and 8; and as shown in Fig. 12, it may yield further improvements.

5.2.4. On the need for non-naive heuristics

Up to now, we have concentrated on experiments that can provide evidence on the higher efficiency of ILS over Greedy and Irid-

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**Fig. 7.** Percentage of $DM(G)$ reduction for $M = 5, 10$ and 15 when $\varepsilon = 20\%$. 

Fig. 8. Percentage of $RT(G)$ reduction for $M = 5, 10$ and $15$ when $\varepsilon = 20\%$.

Fig. 9. Percentage of $DM(G)$ reduction for the Small-A (top) and Large-E (bottom) DAGs when running ILS for different $M$ (horizontal axis), $\varepsilon$ and $\beta$ values.
Fig. 10. Percentage of $RT(G)$ reduction for the Small-A (top) and Large-E (bottom) DAGs when running ILS for different $M$ (horizontal axis), $\varepsilon$ and $\beta$ values.

Fig. 11. Percentage of $DM(G)$ reduction for the Small-A (top) and Large-E (bottom) DAGs when running ILS for different $M$ (horizontal axis), $\varepsilon$ and $d$ values.

Fig. 12. Percentage of $DM(G)$ reduction for the Small-A (top) and Large-E (bottom) DAGs when running ILS on top of Iridium, a random Solution and Greedy for different $M$ (horizontal axis) and $\varepsilon$ values.
ium; improvements over the latter can be 1-2 orders of magnitude. A question may arise as to whether following a simple approach, such as gathering all data in a single DC, can yield better results. To test this hypothesis, in our last set of our experiments, we tried totally removing a DC rather than decreasing its task allocation proportion while making sure that at least one DC is working, i.e., \( \beta \) was set to 1. We also tested running all the jobs in only one DC. The experiments were performed on the Small-A, Large-A and Large-E DAGs. Running all the tasks in one DC means that the data (except for the source jobs) will end up being in that DC. The reduction for Large-E when using ILS or the one DC execution is up to 99% both for traffic and time reduction. For the linear DAGs like Small-A and Large-A the reductions are not that high. As we can see in Fig. 14 and Fig. 15, the naive solution of running all the jobs in one DC is the most beneficial regarding the traffic reduction by an average of 48% while the running time reduction is only 3.3%. Our technique, which gradually removes DCs using ILS, is more beneficial regarding the running time with 43.5% but less beneficial on data traffic with 32.5% of reduction. However, this means that our technique is applicable when we set \( \epsilon < -0.1 \), and in general, yields better improvements on a combined metric that considers \( DM(G) \) and \( RT(G) \) as of equal importance. More specifically, the ratio of the \( RT(G) \) reduction to the \( DM(G) \) reduction is 43.5/32.5 = 1.33 in our case, whereas only 0.067 for the naive solution. This justifies the need to develop more advanced solutions to the problem of bi-objective task allocation in geo-distributed flows.

5.2.5. Summary
The main observations are summarized as follows:

1. ILS induces significant larger reduction in \( DM(G) \) and \( RT(G) \) than Greedy. Specifically, ILS succeeds an average of 44% reduction in \( DM(G) \) while Greedy can reduce it by only 12.4%.
2. ILS achieves most of the time both \( RT(G) \) and \( DM(G) \) reduction showing that Iridium’s task placement is not optimal for complex graphs and that re-arranging the tasks between DCs will likely improve both metrics. In our experiments, ILS decreases time by an average 37%.
3. The \( \beta \) parameter is of high significance. In our experiments, we showed that removing 1/2 of its tasks is more beneficial than removing smaller proportions, i.e., 1/3, 1/4, 1/5. Removing larger proportions has a bigger effect on the total allocation plan thus providing a more beneficial solution. Specifically, \( \beta = 1/2 \) is on average, 30% more beneficial on data traffic reduction and 55% more beneficial on running time reduction than \( \beta = 1/5 \).  
4. ILS and Greedy can be combined, in the sense that Greedy can serve as the initial allocation further refined by ILS. A complete solution is to run ILS on top of both Greedy and Iridium; running ILS on top of a random initial allocation is always inferior.
5. Running a job in fewer DCs is in general more effective than using all the DCs. In some cases running all the jobs in one DC is even more beneficial. In our experiments we found that running all the jobs in one DC from the start is more beneficial regarding the traffic reduction but gradually removing the DCs using ILS is more beneficial when taking into consideration both time and traffic reduction. Therefore, our solutions are the only option for \( \epsilon < -0.1 \).
6. The DAGs which benefit more from our algorithms are the larger and more complex ones like those of the (C), (D) (E) types, with the latter having the highest improvements.
5.3. Spark implementation details and experiments on a real cluster

Our approach has been incorporated into Apache Spark 2.3.2. To enforce our own task placement, we override the TaskSchedulerImpl class, where we disable the shuffling of the offers the executors make for a task. We also edited the TaskSetManager class to set the task locality to “Any” and thus prevent Spark from deciding a placement for the tasks based on the data location.

The real experiments complement the simulated ones only with regards to the RT(G) value; the DM(G) improvements in a real setting are exactly the same as in the simulations. We use three machines, and we examine chain workflows of Type (A), where, in each stage, data is simply repartitioned with selectivity set to 1. The number of nodes in the DAG is initially set to 7 (repartitioning cannot be enforced to the first one), and the input size is 143.6 MB. Table 4 shows the network capacity in four settings. The data allocations for each Spark stage are estimated offline before the execution begins.

In Fig. 16, we compare the estimated RT reduction that ILS achieves over Iridium against the real reduction observed in Spark. On the left hand-side, we observe that the slowest the network, the highest the actual reduction in RT(G). Then, we keep the Case-B in the table, and we modify the DAG size (see Fig. 16(middle)); the actual reductions are more significant for not very small DAGs. Finally, we modify the input size; as shown in Fig. 16(right), real executions are sensitive to this metric. Overall, we see that the simulations tend to overestimate the RT(G) reductions mainly due to the non-negligible processing cost in practice, but there are cases, where the estimates are accurate. In the real experiments, we observed RT(G) reductions up to 51%, but if we exclude the minimum and the maximum values, the mean reduction is 13.75%.

Regarding real times, Table 5 shows the actual running times in our 3-machine cluster. In these cases, the overhead to find the optimized allocation for ILS was 35 s, which means that the overhead is outweighed by the benefits for the input sizes larger than 200 MB. In the next section, we provide further overhead information for larger DAGs.
Table 5
Real times referring to Fig. 16(right).

<table>
<thead>
<tr>
<th>Size (in MBs)</th>
<th>Iridium time (in mins)</th>
<th>ILS time (in mins)</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>0.3</td>
<td>0.23</td>
</tr>
<tr>
<td>87</td>
<td>1.2</td>
<td>0.58</td>
</tr>
<tr>
<td>144</td>
<td>2.6</td>
<td>2.2</td>
</tr>
<tr>
<td>288</td>
<td>4.8</td>
<td>4.2</td>
</tr>
<tr>
<td>689</td>
<td>7</td>
<td>6.3</td>
</tr>
</tbody>
</table>

Table 6
Running times of the algorithms for different M values (in s).

<table>
<thead>
<tr>
<th>Algorithm \ M</th>
<th>Small A</th>
<th>Medium C</th>
<th>Large E</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Iridium</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Greedy (75 iterations)</td>
<td>68</td>
<td>72</td>
<td>78</td>
</tr>
</tbody>
</table>

5.4. Optimization overhead

To assess the runtime overhead of our solutions, we conducted experiments on a machine with i7-4510U CPU at 2.00 GHz with 8 GB of RAM. The running time of each algorithm is presented in Table 6, where we can see that ILS is significantly slower than the other techniques, but still, it runs in less than 3 minutes, which renders it a practical option for data-intensive flows, which typically have larger running times (in general, if the running time is lower, then the number of iterations can be decreased).

6. Discussion

This work deals with the problem of minimizing both the total traffic and the communication-bounded flow execution time in multi-stage geo-distributed data flows. We propose a fast greedy solution and a slower, but more efficient stochastic solution. The latter can achieve significant average reductions of 44% and 37% regarding the two metrics, respectively, compared to the Iridium proposal [2]. In specific cases, the improvements can reach 1-2 orders of magnitude. Moreover, we show that a hybrid scheme for the initial allocation refined by the stochastic solution is preferable. Further, we argue that both using all data centers and using only a single one are inferior to our techniques, which follow a middle approach. We believe that this insight is a valuable contribution of our work, since it essentially advocates to take a critical stand on the broadly spread claim that transferring distributed data to a single or fewer places is too costly. Our solution is implemented and tested in Spark as well.

Our work can be extended in several ways. Two promising directions for future work is to extend our solutions for the cases where the processing capacity of a data center is limited and to account also for the processing cost on the data centers, which is now assumed to be negligible compared to the data transmission time. Another line of research could deal with optimizing for multiple queries, which relates also to the issue of revising the initial data allocation. Finally, since our solutions rely on accurate statistics, developing robust techniques that can tolerate inaccuracies in statistical metadata is important.

References