Towards Reliable (and Efficient) Job Executions in a Practical Geo-distributed Data Analytics System

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Abstract

Geo-distributed data analytics are increasingly common to derive useful information in large organisations. Naive extension of existing cluster-scale data analytics systems to the scale of geo-distributed data centers faces unique challenges including WAN bandwidth limits, regulatory constraints, changeable/unreliable runtime environment, and monetary costs. Our goal in this work is to develop a practical geo-distributed data analytics system that (1) employs an intelligent mechanism for jobs to efficiently utilize (adjust to) the resources (changeable environment) across data centers; (2) guarantees the reliability of jobs due to the possible failures; and (3) is generic and flexible enough to run a wide range of data analytics jobs without requiring any changes.

To this end, we present a new, general geo-distributed data analytics system, HOUTU, that is composed of multiple autonomous systems, each operating in a sovereign data center. HOUTU maintains a job manager (JM) for a geo-distributed job in each data center, so that these replicated JMs could individually and cooperatively manage resources and assign tasks. Our experiments on the prototype of HOUTU running across four Alibaba Cloud regions show that HOUTU provides nearly efficient job performance as in the existing centralized architecture, and guarantees reliable job executions when facing failures.

1 Introduction

Nowadays, organizations are deploying their applications in multiple data centers around the world to satisfy the latency-sensitive requirements [14, 22, 37, 13]. As a result, the raw data – including user interaction loggings, compute infrastructure monitoring, job traces – is generated at geographically distributed data centers. Analytics jobs on these geo-distributed data are emerging as a daily requirement [26, 40, 46, 49, 29, 39, 45, 47, 28, 20].

Minimizing response time and maximizing throughput of these analytics jobs are important in daily business, because they usually support the real-time decisions and online predictions. However, this issue faces the unique challenges of wide area network (WAN) bandwidth limits, legislative and regulatory constraints, unreliable runtime environment, and even monetary costs.

Existing approaches optimize tasks and/or data placement across data centers so as to improve data locality [35, 46, 29, 39, 45, 47]. However, all previous works employ a centralized architecture where a monolithic master controls the resources of the worker machines from all data centers, as shown in Fig. 1(a). We argue that possible regulatory constraints prevent us to do so. More and more regions are establishing laws to restrict the data movement [6, 42, 11] and restrict IT resources from being controlled by other untrusted parties in the shared environment [19] (§2.1). An alternative way is to deploy an autonomous data analytics system per data center (as shown in Fig. 1(b)), and extend the original system functionalities to coordinate for geo-distributed job executions. We explore this decentralized architecture and its potentialities, making it possible for a job to acquire resources from remote data centers which respects to the regulatory constraints.

In addition, most existing works make the assumption that the runtime environment of WAN is stable. This may not accurately conform to the reality [27, 33], and our experiments verify that WAN bandwidth varies even in a short period (§2.2). Hence, this restriction does not allow...
us to explicitly formulate WAN bandwidth as a constant.

On the other hand, for most organizations who have the geo-distributed data analytics requirement, perhaps the most convenient way is to purchase public cloud instances. Decisions must be made between choosing reliable (Reserved and On-demand) instances and unreliable (Spot) instances, due to the monetary cost and job reliability demands. Spot market (the latter) prices are often significantly lower – by up to an order of magnitude – than fixed (the former) prices for the same instances with a reliability Service Level Agreement (SLA) (§2.3). But, is it possible for cloud users to obtain reliability from unreliable instances with a reduced cost? There are positive answers by designing user bidding mechanisms [48, 54], while we explore the answer in a system way, by providing job-level fault tolerance.

Our goal in this new decentralized and changeable/unreliable environment is to design new resource management, task scheduling and fault tolerance strategies to achieve reliable and efficient job executions.

To achieve this goal, such a system needs to address three key challenges. First, we need to find a scheduling strategy that can dynamically adapt scheduling decisions to the changeable environment. This is difficult because we do not assume job characteristics as a priori knowledge [34], or use offline analysis [44] for its significant overhead for our exploratory setting. Second, we need to implement fault tolerance mechanism for jobs. Though existing frameworks like MapReduce [21], Dryad [31] and Spark [51] tolerate task-level failures, the job-level fault tolerance is absent. While in the unreliable setting, the two types of failures have the same chance to occur. Third, we need to design a general system that efficiently handle geo-distributed job executions without requiring any job description changes. This is challenging because data can disperse among sovereign domains (data centers) with regulatory constraints.

In this work, we present HOUTU\(^1\), a new general geo-distributed data analytics system that is designed to efficiently operate over a collection of data centers. The key idea of HOUTU is to maintain a job manager (JM) for the geo-distributed job in each data center, and each can individually assign tasks within its own data center, and cooperatively assign tasks between data centers. This differentiation allows HOUTU to run conventional task assignment algorithms within a data center [50, 34, 53]. At the same time, across different data centers, HOUTU employs a new work stealing method, which converts the task steals to node update events with respect to data locality constraints.

For resource management, we classify three cases where each job manager could independently either request more resources, or maintain current resources, or proactively release some resources. The key insight here is using nearly past resource utilization as feedback, irrespective of the prediction of future job characteristics. Even without the future job characteristics, when cooperating with our new task assignment method, we theoretically prove (under some conditions) the efficiency of job executions by extending the very recent result [53] (§4.4).

Each replicated JM keeps track of the current process of the job execution. We carefully design what need to be included in the intermediate information, which can be used to successfully recover the failure, of even the primary JM.

We build HOUTU in Spark [51] on YARN [43] system, and utilize Zookeeper [30] to guarantee that the intermediate information is consistent among job managers in different data centers. We deploy HOUTU across four regions on Alibaba Cloud. Our evaluation with typical workflows including TPC-H and machine learning algorithms shows that, HOUTU: (1) achieves nearly efficient job performance as in the centralized architecture; (2) guarantees reliable job executions when facing job failures; and (3) is very efficient in reducing monetary cost.

We make three major contributions:

- We present a general decentralized data analytics system to respect the possible regulatory constraints and changeable/unreliable runtime environment. The key idea is to provide a job manager for the geo-distributed job in each data center. The system is general and flexible enough to deploy a wide range of data analytics jobs while require no change to the jobs themselves (§3.1).

- We propose resource management strategy Af for each JM which exploits resource utilization as feedback. We design task assignment method Parades which combines the assignment within and between data centers. We prove Af + Parades guarantees efficiency for geo-distributed jobs with respect to makespan (§4). We carefully design the mechanism of coordinating JMs, and the intermediate information to recover a failure (§3.2).

- We build a prototype of our proposed system using Spark, YARN and Zookeeper as blocks, and demonstrate its efficiencies over four geo-distributed regions with typical diverse workloads (§5 and §6). We show that HOUTU provides efficient and reliable

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\(^1\) HOUTU is the deity of deep earth in ancient Chinese mythology who controls lands from all regions.
job executions, and significantly reduces the costs for running these jobs.

2 Background and Motivation

This section motivates and provides background for HOUTU. §2.1 describes the existing and upcoming legislative and regulatory constraints which prevent us to employ a centralized architecture. We measure the scarce and changeable WAN bandwidth between all pairs of AliCloud in four regions in §2.2. We investigate a way to reduce monetary cost using Spot instances in §2.3.

2.1 Regulatory constraints

Through it is efficient to employ data analytics system in clouds, many organisations still decline to widely adopt cloud services due to severe confidentiality and privacy concerns [16], and explicit regulations in certain sectors (healthcare and finance) [15]. Local governments start to impose constraints on raw data storage and movement [6, 11, 42]. These constraints may exclude the solutions that moves arbitrary data from bottleneck data centers to any other data centers [39, 45].

Public clouds allow users to instantiate virtual machines (instances) on demand. In turn, the use of virtualization allows third-party cloud providers to maximize the utilization of their sunk capital costs by multiplexing many customer VMs across a shared physical infrastructure. However, this approach can introduce new vulnerabilities. It is possible to map the internal cloud infrastructure, identify where a particular target VM is likely to reside, and then instantiate new VMs until one is placed co-resident with the target, which can then be used to mount cross-VM side-channel attacks to extract information from a target VM [41, 19]. The attack amplifier turns this initial compromise of a host into a platform for launching a broad, cloud-wide attack [18].

Hence, cloud providers and exiting works are proposing solutions in which a group of instances have their external connectivity restricted according to a declared policy as a defense against information leakage [52, 3, 2]. As a result, these upcoming regulatory constraints lead to deploying an autonomous system in each data center, which contains the complete stack of data analytics softwares.

We follow exactly this guideline, propose a decentralized architecture (Fig. 1(b)) and explore how resource management and task scheduling should be performed to support geo-distributed job executions. We speculate that derived information, such as aggregates and reports (which are critical for business intelligence but have less dramatic privacy implications) may still be allowed to cross geographical boundaries.

2.2 Changeable environment

It is well known that WAN bandwidth is a very scarce resource relative to LAN bandwidth. To quantify WAN bandwidth between data centers, we measure the network bandwidth between all pairs of AliCloud in four regions including NorthChina-3 (NC-3), NorthChina-5 (NC-5), EastChina (EC-1), and SouthChina-1 (SC-1). We use iPerf [8] to measure the network bandwidth of each pair of different regions for three rounds, each for 5 minutes. Fig. 2 shows the average and the standard deviation between each pair of different regions.

The WAN bandwidth between data centers is 10x smaller than the LAN bandwidth within a data center on average. What we emphasize is that the WAN bandwidth varies between different regions even in a small period. The standard deviation can be as much as 30% of the available WAN bandwidth itself. This fluctuation observation also coincides with [27, 33].

Furthermore, it may not always be the same resource – WAN bandwidth – that causes runtime performance bottlenecks in wide-area data analytic queries. The types of resource that cause performance bottlenecks may even vary over time at runtime [47], thus the uncertainties do not allow us to assume the capacities of resources (e.g. network, compute) as constant in mathematical programming. We explore mechanisms that can make dynamic scheduling decisions to the changeable environment.

2.3 Spot instance: towards reducing cost

Cloud computing providers may offer different SLAs at different price points so that users can control the value transaction at a fine level of granularity. Besides offering reliable (Reserved and On-demand) instances, cloud providers such as Google Cloud Platform (GCP) [7], Amazon EC2 [5], Microsoft Azure [10] and Alibaba

|        | NC-3     | NC-5     | EC-1     | SC-1     |
|--------|----------|----------|----------|----------|
| NC-3   | (821.95) | (79.22)  | (78.24)  | (79.24)  |
| NC-5   | --       | (820.115)| (103.28) | (71.28)  |
| EC-1   | --       | --       | (848.99) | (103.30) |
| SC-1   | --       | --       | --       | (821.107)|

Figure 2: Measured network bandwidth between AliCloud in four different regions. The entry is of form (Average, Standard deviation) Mbps.
Figure 3: Three pricing ways to pay for an instance with <4 vCPU, 16 GB memory> in GCP, EC2, AliCloud and Azure (in USD)

Cloud [1] also offer “Spot instances”\(^2\) where resources (at a cheaper price) without a reliability SLA. When a user makes a request for a spot instance having a specific set of characteristics (e.g. <4 vCPU, 16 GB memory>), he/she includes a maximum bid price indicating the maximum that the user is willing to be charged for the instance. Cloud providers create a market for each instance type and satisfies the request of the highest bidders. Periodically, cloud providers recalculate the market price and terminate those instances whose maximum bid is below the new market price. Because the Spot instance market mechanism does not provide a way to guarantee how long an instance will run before it is terminated as part of an SLA, Spot market prices are often significantly lower than fixed prices for the same instances with a reliability SLA (by up to 10x lower than On-demand price, and 3x lower than Reserved price, as shown in Fig. 3).

Is it possible to deploy data analytics system using Spot instances and guarantee reliable job executions with reduced cost? To address this question, it requires to tolerate job-level and task-level failures due to the terminations of unreliable instances, where the former one relates to the failure of the job manager. Because both job managers and tasks run in unified containers, the two types of failures have the same opportunity to occur. Unfortunately, while the task-level fault-tolerance is implemented in current systems [21, 51, 31], these systems do not tolerate job manager failures except for restarting them.

We extend the current system functionalities to implement the job-level fault-tolerance, and obtain (highly probabilistic) reliability of job executions in unreliable environment with lower monetary costs.

3 System Overview

We first provide an overview of the HOUTU architecture and a job’s lifecycle in HOUTU (§3.1). Next, we elaborate how a job acts in normal operation and fault recovery (§3.2).

3.1 HOUTU architecture

As shown in Fig. 4(a), HOUTU is of the decentralized architecture, which is composed with several autonomous systems, deployed in geographically distributed data centers. Each system has the ability to run conventional single-cluster jobs, and also to cooperate with each other to support geo-distributed job executions, while we focus the latter in this work.

As stated in §1, HOUTU is a general system that efficiently handle geo-distributed job executions without requiring any job description changes. We speculate that users have the knowledge of how data is distributed across several data centers. The users specify the data locations “as if” in a centralized architecture, except with different “masters”. In the SQL example of Fig. 5, three tables are in different data centers, and the job derives statical information from all these tables. HOUTU will automatically support the execution of a job described in this way.

Next, we present the a job’s lifecycle, following the steps of Fig. 4(a).

The job submission and job manager generations: Suppose a user submits the DAG job to a chosen master (step 0). We use DAG to refer to a directed acyclic graph, where each vertex represents a task and edges encode input-output dependencies. The master would resolve the job description and generate corresponding job managers for it (step 1). It directly generates a primary job manager (pJM) within its own cluster (step 2). For the remote resources, the master forwards the job description to the remote masters (step 2a) and tells them to generate semi-active job manager (sJM) for it (step 2b) (§3.2). Resource request and task executions: Further, to obtain compute resources (task executors\(^3\)), the job managers independently send the requests to their local masters (step 3). The masters schedule resources to the JMs according to their scheduling invariants, and signal this by returning to the JMs containers that grant access to such resources (step 4). After that, the JMs send the tasks to run in the containers (step 5). As the DAG job is dynamically unfolded and resource requests of the job usually are not satisfied in a single wave, JMs often repeat steps 3 – 5.

\(^2\)We use this term from EC2, while it is called “preemptible VM” in GCP, “bidding instance” in AliCloud, and “low-priority VM” in Azure.

\(^3\)Unless otherwise specified, we use the term “container” and “executor” interchangeably.
agers, and then the job managers
initial generated job managers hold the DAG structure of the job.

between data centers in
DAG, and how to assign tasks within a data center and
sources without further characteristics of the unfolding
for multiple times.

We leave the design of how job managers request re-
source utilization feedback (purple solid line) (§4.2).

After a task completes its computation on a partition
data, it reports to its job manager (pJM or sJM) about
the output partition location. The job manager then col-
lects the partition location information in its cluster, modi-
ifies the partitionList, and then notifies other job managers
to keep the consistency of partitionList. Besides the par-
titionList, HOUTU includes jobId, stageId, executorList
(available executors from all data centers, including
JMs and their associated roles), and taskMap (which task
should be assigned by which JM) in a job’s intermediate
information (Fig. 4(b)). HOUTU maintains a replica-
tion of the intermediate information in each data center.

Since the job managers operate synchronously, when
the job completes, all of them will proactively release their
resources as well as themselves to their data centers.

3.2 A job in HOUTU

We show how the primary job manager (pJM) and semi-
active job managers (sJMs) coordinate to execute a job.

3.2.1 Normal operation

In normal operation, there is exactly one pJM and all of
the other servers are sJMs in a job. When the master (to
which a user submit the job) forwards the request (step 2a
in Fig. 4(a)), it includes the job description. Thus, all the
generated job managers hold the DAG structure of the job.

When the job managers are in position, the pJM first
decides the initial task assignment among the job man-
gers, and then the job managers cooperatively schedule
and generate tasks to execute (dot line in Fig. 4(b)) (§4.3).

We call each sJM semi-active because it is not totally un-
der control of the primary job manger, and it has freed-
dom to determine the task assignment in its own cluster
(dash line), to coordinate with other sJMs about task as-
ignment, and to manage its compute resources according
to resource utilization feedback (purple solid line) (§4.2).

3.2.2 Fault recovery

As stated in §2.3, we focus on in this work the recovery of
job-level failures, which is the failures of job managers.

When a semi-active job manager fails because of the un-
predictable termination of its host, the primary job
manager will notice it and then send a request through its
local master to generate a new sJM in the remote data cen-
ter (like steps 2a and 2b in Fig. 4(a)). This sJM starts
with the original job description and the intermediate in-
formation in its cluster and recognises its role (as semi-active).
It inherits the containers belonging to the previous sJM,
and continues to operate as in normal.

If the primary fails, the semi-active job managers will elect a new primary using the consistent protocol (in Zookeeper). The new pJM updates and propagates the intermediate information about its role change. Next, the new primary continues the process of the job, operates in normal and generates a new semi-active job manager to replace the failed pJM as above.

We assume that all the job managers would not fail simultaneously. Actually, it is of particular interest to study the problem which guarantees deterministic reliability of a job execution in the mixed environment (with reliable and unreliable instances) and minimizes the total monetary cost, however this is out of the scope of this work.

4 Design

In this section, we first provide the problem statement of optimizing efficiency of jobs (§4.1). Next, we show how the job managers use resource utilization feedback to request or release resources (§4.2). Then, we describe how the job managers schedule tasks within and between data centers (§4.3). Finally, we theoretically analyze the performance of the algorithms (§4.4).

4.1 Problem statement

Resources in HOUTU are scheduled in terms of containers (corresponding to some fixed amount of memory and cores). Instead of assuming the priori knowledge of complete characteristics of jobs [23, 24, 25], which restricts the types of workloads and incurs offline overheads, we rely on only partial prior knowledge of a job (the knowledge from available stages). In the example of Fig. 6, only the task information (including the input data locations, fine-grained resource requirements, and process times) in Stage 0 is currently known, while the task information in Stage 1 and Stage 2 is currently unknown because they have not been released yet. We consider that tasks in the same stage have identical characteristics, which conforms to the fact in practical systems as they perform the same computations on different partitions of the input.

In the scenario where multiple DAG jobs arrive and leave online, we are interested in minimizing the makespan and average job response time\(^4\). Please refer to Appendix A for the problem formulation. HOUTU applies Af for each JM to manage resources, and Parades in each JM to schedule tasks, which we will demonstrate in next two subsections, respectively.

\(^4\)The response time of a job is the duration time from its release to its completion.

4.2 Resource management using Af

Resources in a data center are scheduled by the job scheduler to sub-jobs between periods, each of equal time length \(L\). We denote the sub-job to the collection of tasks of a job that are executed in the same data center (and handled by the same job manager). Fig. 6 shows an example of sub-job partition with dot-line cycles.

For each sub-job \(J^i\) of job \(J\), its job manager (pJM or sJM) enforces Af (Algorithm 1) to determine the desire number of containers for next period \(d(J^i, q)\) based on its last period desire \(d(J^i, q - 1)\), the last period allocation \(a(J^i, q - 1)\), the last period resource utilization \(u(J^i, q - 1)\) and waiting tasks.\(^5\) \(u(J^i, q - 1)\) corresponds to the average resource utilization in period \(q - 1\), and can be measured by the monitoring mechanism.

Consistent with [12], we classify the period \(q - 1\) as satisfied versus deprived. Af compares the job’s allocation \(a(J^i, q - 1)\) with its desire \(d(J^i, q - 1)\). The period is satisfied if \(a(J^i, q - 1) = d(J^i, q - 1)\), as the sub-job \(J^i\) acquires as many containers as it requests from the job scheduler. Otherwise, \(a(J^i, q - 1) < d(J^i, q - 1)\), the period is deprived. The classification of a period as efficient versus inefficient is more involved than that in [12].

\(^5\)We omit \(J^i\) in Algorithm 1 for brevity.
Algorithm 2 Parades (applied by each job manager)

1: procedure ONUPDATE(n, δ, τ)
2:  For each t_ij, increase t_ij.wait by the time since last event UPDATE; cont ← true
3:  if no waiting task then
4:     t = STEAL(n);
5:     tlist.add(t); n.free ← t.r; cont ← false;
6:  while n.free > 0 and cont do
7:     cont ← false;
8:  if there is a node-local task t_ij on n and n.free ≥ t_ij.r then
9:     t = t_ij
10:    else if there is a rack-local task t_ik on n and n.free ≥ t_ik.r and t_ik.wait ≥ τ · t_ik.p then
11:       t = t_ik
12:    else if there is a task t_il with t_il.wait ≥ 2τ · t_il.p and n.free ≥ 1 − δ then
13:       t = t_il
14:       tlist.add(t); n.free ← t.r; cont ← true;
15:       procedure ONRECEIVESTEAL(n)
16:       return ONUPDATE(n, δ, τ)
17: procedure STEAL(n)
18: for each job manager of the same job do
19:    tlist.add(SENDSTEAL(n))
20: return tlist

Table 1: Explanations of notations

| Notation | Explanation                  |
|----------|------------------------------|
| d(J_j^i, q) | J_j^i’s desire for period q |
| a(J_j^i, q) | J_j^i’s allocation for period q |
| u(J_j^i, q) | J_j^i’s resource utilization in period q |
| δ         | the utilization threshold parameter |
| ρ         | the resource adjustment parameter |
| τ         | the task waiting time parameter |

Parades (Parameterized delay scheduling with work stealing) is applied by each job manager after the initial assignment. Parades is based on framework of the original delay scheduling algorithm [50], but extends it from two perspectives. When a container updates its status, the algorithm adds the waiting time for each waiting task in the sub-job since the last event UPDATE happened (line 2), followed by the task assignment procedure. Delay scheduling sets the waiting time thresholds for tasks as an invariant, while we modify the threshold for each task to be linearly dependent of its processing time (which is known), under the intuition of that “long” tasks are tolerant for waiting for longer time to acquire their preferred resources. On the other hand, if there is no waiting task, the job manager becomes a “thief” and tries to steal tasks from other “victim” job managers in the same job (line 4). Each victim job manager will handle this steal as a UPDATE event (line 16).

Parades operates as follows in task assignment procedure: It first checks whether there is a node-local task waiting, which means the free container is on the same server as the task prefers. Assigning the task to its preferred server which containing its input data helps in reducing data transmission over the network. We use n.free to denote the free resources on container n. Secondly, the algorithm would check whether there is a rack-local task for the n, as the container shares the same rack as the task’s preferred server. If the task has waited for more than the threshold time (τ · t_ij.p), and the container has enough free resources, we assign the task to the container. Finally, when a task has waited for long enough time (2τ · t_ij.p), and n.free ≥ 1 − δ, we always allow the task could be assigned if possible. When n.free ≥ 1 − δ, the utilized resource of the container n < δ. We assume t_ij.r + δ ≤ 1, for each i, l, as the upper bound for task resource requirement.

Please refer to Table 1 for the involved notations in our algorithms and their explanations.
4.4 Analysis of the algorithms

To prove the proposed algorithms guarantee efficient performance for online jobs, we settle the job scheduler employed in each data center as the fair scheduler [4, 9], perhaps the most widely used job scheduler in both industry and academia. Once there is a free resource, the fair scheduler always allocates it to the job which currently occupies the fewest fraction of the cluster resources, unless the job’s requests have been satisfied.

We prove the following theorem about the competitive efficiency of makespan. Specifically, we extend the very recent result [53] about the efficiency of jobs scheduled by Af algorithm and parameterized delay (Pdelay) scheduling algorithm in a single data center.\(^6\) Please see Appendix B for the proof sketch. We are still working on the provable efficiency about the average job response time.

**Theorem 1** When multiple geo-distributed DAG jobs arrive online and each data center applies fair job scheduler, the makespan of these jobs applying Af + Parades, is \(O(1)\)-competitive.

5 Implementation

We implement HOUTU using Apache Spark [51], Hadoop YARN [43] and Apache Zookeeper [30] as building blocks. We make the following major changes:

**Monitor mechanism:** We estimate the dynamic resource availability on each container by adding a resource monitor process (in NodeManager component of YARN). The monitor process reads resource usages (e.g., CPU, memory) from OS counters and reports them to its job manager. Each job manager and its per-container monitors interact in an asynchronous manner to avoid overheads.

**Parameterized delay scheduling:** Based on the fact that tasks in a stage have similar resource requirements, we estimate the requirements using the measured statistics from the first few executions of tasks in a stage. We continue to refine these estimations as more tasks have been measured. We estimate task processing time as the average processing time of all finished tasks in the same stage. We modify the original implementation of delay scheduling in Spark to take \(\tau\) as a parameter read from the configuration file.

**How the job managers coordinate with each other?** As stated in §3.2.1, we use Zookeeper to synchronize job managers in the same job. Specifically, when the pJM determines the initial task assignment, it writes this information to taskMap (Fig. 4(b)). sJMs will notice this modification and begin their task assignment procedures using Parades (§4.3). If a job manager successfully steals a task from another, it also needs to modify the corresponding item in taskMap. After a task completes, it reports to its job manager about the output location, who will then propagate the location information in partitionList among other job managers.

**How a new job manager inherits the containers belonging to the failed one?** We modify YARN master to allow to grant tokens to the new generated job manager with the same jobId as the failed one. Then, the new job manager could use these tokens to access the corresponding containers.

- **Af:** We continuously (per second) measure the container utilizations in a sub-job \(J^t\) in a period \(q\) of length \(L\), and calculate the average at the end of the period. We acquire the desire number of containers for the next period \(d(q + 1)\) by Af. If \(d(q + 1) \geq d(q)\), we directly update the desire and push this new desire to the job scheduler. When \(d(q + 1) < d(q)\), the problem is involved, since we should decide \textit{Which} containers should be killed, and \textit{when} the kill should be performed? We aggressively kill the several containers which firstly become free. We add the control information through the job manager in Spark to negotiate resources with YARN.

6 Experimental Evaluation

In this section, we first present the methodology in conducting our experiments (§6.1). Then, we show the efficient job performance HOUTU guarantees in both normal operation and changeable environment (§6.2), and analyze the monetary costs of HOUTU and other deployments when running the same workloads (§6.3). Finally, we verify the ability of recovering of job manager failures in HOUTU (§6.4) and measure the overheads that it introduces in detail (§6.5).

6.1 Methodology

**Testbed:** We deploy HOUTU to 20 machines spread across four AliCloud regions as we show in §2.2. In each region, we start five machines of type n4.xlarge or n1.large, depending on their availability. Both types of instances have 4 CPU cores, 8GB RAM and run 64-bit Ubuntu 16.04. In each region, we choose one On-demand instance as the master and four Spot instances as workers.

**Workload:** We use workloads for our evaluation including WordCount, TPC-H benchmark, Iterative ma-
shows two types of costs in different deployments. First, we find that HOUTU has approximate performance compared with the centralized architecture with start-of-the-art dynamic scheduling mechanism. This approximation is due to that we allow job managers in a job to share resources across data centers by work stealing (Parades). Second, when compared with the decentralized architecture with static scheduling algorithm, HOUTU has 29% improvement in terms of average job response time, and 31% improvement in terms of makespan. This gain comes from the use of adaptively scheduling mechanism based on utilization feedback (Af).

To further demonstrate that HOUTU guarantees efficient job performance in a changeable environment, we intentionally inject workloads to consume spare resources in data centers and see how a job reacts to this variation. Fig. 9 shows the cumulative running tasks of a job execution in different scenarios and mechanisms. In Fig. 9(a), a job executes normally and completes at time 115. While in Fig. 9(b) and Fig. 9(c), we inject workloads into three data centers NC-3, EC-1 and SC-1 to use up almost all spare resources in these data centers at time 100 after a job submission. Fig. 9(b) demonstrates that work stealing mechanism ensures that the job manager in NC-5 gradually steals tasks from the other resource-limited data centers as the new stages of the DAG job become available. However, without work stealing, the pJM assigns tasks only according to the data distribution (initial assignment), which then leads to that the jM in resource-limited data centers would queue the tasks to be executed. As shown in Fig. 9(c), the queueing delays the job. Job response times in last scenarios are 183 and 333 seconds, respectively.

### 6.3 Cost analysis

In this subsection, we configure the centralized architecture with On-demand instances, while we keep the decentralized architecture configuration with Spot instances (except the masters). We use the same workloads as in Fig. 8, and calculate the monetary costs in different deployments. Costs are divided into machine cost and data transfer cost across different data centers.

Fig. 10 shows two types of costs in different deployments normalized with the cost in cent-stat. First, we observe HOUTU is very effective in reducing the machine cost of running geo-distributed jobs, which is 90% cheaper than the cost in cent-stat. Not surprisingly, the major cost saving comes from the use of Spot instances. Second, HOUTU has fewer data transfer costs.

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3In AliCloud [1], the price of data transfer across data centers is 0.13$/GB, while it is free to transfer data within a data center.
pared with centralized architectures. This is because centralized architectures do not distinguish machines in different data centers; while HOUTU differentiates task assignment within a data center and between data centers, and a task steal happens only after the thief job manager finishes its own tasks. HOUTU saves about 20% communication cost compared with cent-stat.

### 6.4 Fault recovery

One of our major design considerations of HOUTU is to ensure that a job could recover from a failure due to the unreliable environment and continue to execute. To understand the effectiveness of our proposed mechanism, we respectively run a job in HOUTU and cent-dyna, and we manually terminate the host (VM) where the job manager resides at 70 seconds after its submission.

We count the number of containers belonging to the job. Fig. 11 shows the process of the job execution experiencing a job manager failure. In Fig. 11(a), we kill the VM which hosts the pJM, and after 10 seconds we see a new sJM substitutes the failed pJM. The sJM then inherits the old containers and continues its work. While in Fig. 11(b), we kill a sJM and see the similar process. The interval time is always lower than 20 seconds in our extensive experiments. The job response times in two scenarios are 147 seconds and 154 seconds, respectively. However, in the centralized architecture, the failure of a job manager leads to the resubmission of the job, which wastes the previous computations. The job response time is 299 seconds in the last case, which is significantly longer than the times in two executions in HOUTU.

### 6.5 Overhead

We measure overheads of HOUTU from two perspectives. First, we collect the intermediate information of jobs from four workloads on large input datasets, and measure their sizes during their executions. Fig. 12(a) plots the 25th percentile, median and 75th percentile sizes for each workload in the corresponding box. We find the average intermediate information sizes for the four workloads are 43.1 KB, 43.4 KB, 37.8 KB and 30.8 KB, respectively, which are small enough to use Zookeeper to keep them consistent.

Second, we measure the time costs of mechanisms that HOUTU introduces. For the Af overhead, it just maintains the update operation and incurs negligible costs. Compared to the default implementation in YARN, we add the monitoring mechanism in each container process, which has moderate overhead. As a job manager incurs transmission delay in work stealing, we find the average delay of the steal message transmissions is 63.53 ms across different system loads.

### 7 Related Work

The research in this work is related to the following.

**Wide-area data analytics:** Prior work establishes the emerging problem of analyzing the globally-generated
data in data analytics systems [46, 29, 39, 45, 47, 28, 20]. These works show promising WAN bandwidth reduction and job performance improvement. SWAG [29] adjusts the order of jobs across data centers to reduce job completion times. Iridium [39] optimizes data and task placement to reduce query response times and WAN usage. Clarinet [45] pushes wide-area network awareness to the query planner, and selects a query execution plan before the query begins. The proposed solutions work in the centralized architecture and assume the WAN bandwidth as constant, however, these may not conform to the practical scenario due to our argument in §2. In contrast, we focus on the design of the decentralized geo-distributed data analytics architecture and requires no modification to the current job descriptions.

**Scheduling in a single data analytics system:** Data-locality is a primary goal when scheduling tasks within a job. Delay scheduling [50], Quincy [32] and Corral [34] try to improve the locality of individual tasks by scheduling them close to their input data. Fairness-quality trade-off between multiple jobs is another goal. Carbyne [24] and Graphene [25] improve cluster utilizations and performances while allowing a little unfairness among jobs. Most of these systems rely on the priori knowledge of DAG job characteristics. Instead, we use utilization feedback to dynamically adjust scheduling decisions with only partial priori knowledge. We extend this mechanism in the context of geo-distributed data centers and allow job managers to cooperate in scheduling tasks.

**Fault-tolerance for jobs in data analytics:** In current systems like MapReduce [21], Dryad [31] and Spark [51], each job manager tracks the execution time of every task, and reschedules a copy task when the execution time exceeding a threshold (straggler). At the level of jobs, the cluster (job scheduler) will resubmit a job when its reports are absent for a while. The resubmitted job starts its execution from scratch, wasting the previous computations. In the relevant grid computing, fault-tolerance of jobs is achieved by checkpointing, which is the collection of process context states [38, 36]. The process context states are stored periodically on a stable storage, which is not applicable in the data analytics systems due to the overhead for each job manager collecting the real-time task states and then persisting them. We include the output location for each task (partitionList) instead of its context state in its intermediate information, which is effective and incurs acceptable overheads as evidenced in our experiments.

**8 Conclusion**

We introduce HOUTU, a new data analytics system that is designed to support analytics jobs on globally-generated data with respect to the practical constraints, without any need to change the jobs. HOUTU provides a job manager for a job in each data center, ensuring the reliability of its execution. We present the strategy for each JM to independently manage resources without complete priori knowledge of jobs, and the mechanism for each JM to assign tasks which can adjust its decisions according to the changeable environment. We experimentally ver-
ify HOUTU’s functionalities to guarantee reliable and efficient job executions. We conclude that HOUTU is a practical and effective system to enable constrained globally-distributed analytics jobs.

A Problem Formulation

Suppose there is a set of jobs \( \mathcal{J} = \{ J_1, J_2, \ldots, J_{|\mathcal{J}|} \} \) to be scheduled on a set of containers \( \mathcal{P} = \{ P_1, P_2, \ldots, P_{|\mathcal{P}|} \} \) from all data centers. These containers are different since they reside in different servers (and different data centers) containing different input data for jobs. Time is discretized into scheduling periods of equal length \( L \), where each period \( q \) includes the interval \([L \cdot q, L \cdot (q + 1) - 1]\). \( L \) is a configurable system parameter.

We model a job \( J_i \) as a DAG. Each vertex of the DAG represents a task and each edge represents a dependency between the two tasks. Each task in a job prefers a unique subset of \( \mathcal{P} \), as the containers in the subset store the input data for the task. For each task \( t_{ij} \in J_i \), we denote by \( t_{ij}.r \) to be the peak requirements. We assume \( 0 \leq t_{ij}.r \leq 1 \), normalized by the container capacity. We also assume \( t_{ij}.r \geq \theta \), where \( \theta > 0 \), i.e., a task must consume some amount of resources. We associate \( t_{ij}.p \) to be the processing time of task \( t_{ij} \). Furthermore, the work of a job \( J_i \) is defined as \( T_1(J_i) = \sum_{t_{ij} \in J_i} t_{ij}.r \cdot t_{ij}.p \). The release time \( r(J_i) \) is the time at which the job \( J_i \) is submitted. A task is called in the waiting state when its predecessor tasks have all completed and itself has not been scheduled yet.

The sub-job \( J^i_j \) of \( J_i \) corresponds to a collection of tasks executing in the data center \( j \). Each job manager handles the task executions of a sub-job in the job manager’s data center. The job managers of a job are oblivious to the further characteristics of the unfolding DAG.

**Definition 1** The makespan of a job set \( \mathcal{J} \) is the time taken to complete all the jobs in \( \mathcal{J} \), that is, \( T(\mathcal{J}) = \max_{J_i \in \mathcal{J}} T(J_i) \), where \( T(J_i) \) is the completion time of job \( J_i \).

**Definition 2** The average response time of a job set \( \mathcal{J} \) is given by \( \frac{1}{|\mathcal{J}|} \sum_{J_i \in \mathcal{J}} (T(J_i) - r(J_i)) \).

The job scheduler of a data center and a job manager interact as follows. The job scheduler reallocates resources between scheduling periods. At the end of period \( q - 1 \), the job manager of sub-job \( J^i_j \) determines its desire \( d(J^i_j, q) \), which is the number of containers \( J^i_j \) wants for period \( q \). Collecting the desires from all running sub-jobs, the job scheduler decides allocation \( a(J^i_j, q) \) for each sub-job \( J^i_j \) (with \( a(J^i_j, q) \leq d(J^i_j, q) \)). Once a job is allocated containers, the job manager further schedules its tasks. And the allocation does not change during the period. Given a job set \( \mathcal{J} \) and container set from all data centers \( \mathcal{P} \), we seek for a combination of a job scheduler (how to allocate resources to sub-jobs), and job managers within each job (how to request resources and how to assign tasks to the given resources), which minimizes makespan and average response time of \( \mathcal{J} \), while satisfying the task locality preferences.

B Efficiency of the Makespan

We first state a theorem from [53] and then use it to prove the efficiency of makespan in the context of geodistributed DAG jobs running in multiple data centers.

**Theorem 2** [53] In a single data center with container set \( \mathcal{P} \), which applies fair job scheduler, when DAG jobs \( \mathcal{J} \) running in it with each applying Adaptive feedback algorithm to request resources and parameterized delay scheduling to assign tasks, the makespan of these jobs is

\[
T(\mathcal{J}) \leq \left( \frac{2}{1 - \delta} + \frac{1 + \rho}{\delta} + \frac{2\tau}{\theta} \right) \frac{|\mathcal{P}|}{|\mathcal{J}|} + L \log_{|\mathcal{P}|} |\mathcal{J}| + 2L.
\]

Assume there are \( k \) data centers, the sub-job set executing in data center \( j \) is \( \mathcal{J}^j \) and there are \( |\mathcal{P}_j| \) containers in date center \( j \). In the \( J_i \) example of Fig. 6, \( J^1_1 \in \mathcal{J} \), \( J^2_2 \in \mathcal{J} \), and \( J^3_3 \in \mathcal{J} \). Denote \( c_i = \frac{1}{|\mathcal{P}_i|}(\frac{2}{1 - \delta} + \frac{1 + \rho}{\delta} + \frac{2\tau}{\theta}) \) and \( d_i = L \log_{|\mathcal{P}_i|} |\mathcal{J}^i| + 2L \).

By directly applying theorem 2, we have for each \( i \),

\[
T(\mathcal{J}^i) \leq c_i \cdot T_1(\mathcal{J}^i) + d_i.
\]

Sum them up, we have

\[
\sum_{i=1}^{k} T(\mathcal{J}^i) \leq c_{\max} \cdot \sum_{i=1}^{k} T_1(\mathcal{J}^i) + \sum_{i=1}^{k} d_i
\]

\[
= c_{\max} \cdot T_1(\mathcal{J}) + \sum_{i=1}^{k} d_i
\]

\[
= c_{\max} \cdot |\mathcal{P}| \cdot \frac{T_1(\mathcal{J})}{|\mathcal{P}|} + \sum_{i=1}^{k} d_i,
\]

in which \( c_{\max} \) is the max of \( c_i \) and the first equality is due to the definition of work. According to the fact \( \sum_{i=1}^{k} T(\mathcal{J}^i) \geq T(\mathcal{J}) \), we have

\[
T(\mathcal{J}) \leq c_{\max} \cdot |\mathcal{P}| \cdot \frac{T_1(\mathcal{J})}{|\mathcal{P}|} + \sum_{i=1}^{k} d_i.
\]
Since $\frac{T^*(J)}{|P|}$ is a lower bound of $T^*(J)$ due to [17], and the number of available containers in all data centers $|P|$ is constant once the system is well configured, we complete the proof of theorem 1.

References

[1] Alibaba Cloud – Pricing. https://ecs-buy.aliyun.com/price.

[2] Amazon Web Services. Amazon virtual private cloud. https://aws.amazon.com/vpc/.

[3] Amazon Web Services. Aws identity and access management (iam). https://aws.amazon.com/iam/.

[4] Apache YARN – Fair Scheduler. http://tinyurl.com/j9vzsl9.

[5] Cloud Services Pricing – Amazon Web Services (AWS). https://aws.amazon.com/pricing/.

[6] European Commission press release. Commission to pursue role as honest broker in future global negotiations on internet governance. https://tinyurl.com/k8xcvy4.

[7] Google Cloud Platform – Price List. https://tinyurl.com/y9nyq68e.

[8] iPerf – The ultimate speed test tool for TCP, UDP and SCTP. https://iperf.fr/.

[9] Max-min fairness. https://tinyurl.com/krkdmho.

[10] Microsoft Azure – Pricing Overview. https://tinyurl.com/zk5kvla.

[11] Personal Data (Privacy) Ordinance. https://tinyurl.com/8617dqg. 2009.

[12] K. Agrawal, Y. He, W. J. Hsu, and C. E. Leiserson. Adaptive scheduling with parallelism feedback. In PPoPP, 2006.

[13] Alibaba. Alibaba cloud available regions. https://tinyurl.com/y84lfshq.

[14] Amazon. AWS global infrastructure. https://tinyurl.com/px6dzut.

[15] G. J. Anna et al. Hipaa regulations-a new era of medical-record privacy? New England Journal of Medicine, 348(15), 2003.

[16] A. Armando, R. Carbone, L. Compagna, J. Cuellar, and L. Tobara. Formal analysis of saml 2.0 web browser single sign-on: Breaking the saml-based single sign-on for google apps. In FMSE, 2008.

[17] T. Brecht, X. Deng, and N. Gu. Competitive dynamic multiprocessor allocation for parallel applications. Parallel Processing Letters, 07(01), 1997.

[18] A. Burtsev, D. Johnson, J. Kunz, E. Eide, and J. Van der Merwe. Capnet: Security and least authority in a capability-enabled cloud. In SoCC, 2017.

[19] R. Buuyaa, J. Broberg, and A. M. Goscinski. Cloud computing: Principles and paradigms, chapter 24: Legal Issues in Cloud Computing. 2010.

[20] L. Chen, S. Liu, B. Li, and B. Li. Scheduling jobs across geo-distributed datacenters with max-min fairness. In INFOCOM, 2017.

[21] J. Dean and S. Ghemawat. Mapreduce: Simplified data processing on large clusters. In OSDI, 2004.

[22] Google. Google data center locations. https://tinyurl.com/n7nthda.

[23] R. Grandl, G. Ananthanarayan, S. Kandula, S. Rao, and A. Akella. Multi-resource packing for cluster schedulers. In SIGCOMM, 2014.

[24] R. Grandl, M. Chowdhury, A. Akella, and G. Ananthanarayan. Altruistic scheduling in multi-resource clusters. In OSDI, 2016.

[25] R. Grandl, S. Kandula, S. Rao, A. Akella, and J. Kulkarni. Graphene: Packing and dependency-aware scheduling for data-parallel clusters. In OSDI, 2016.

[26] A. Gupta, F. Yang, J. Govig, A. Kirsch, K. Chan, K. Lai, S. Wu, S. G. Dhoot, A. R. Kumar, A. Agiwal, S. Bhansali, M. Hong, J. Cameron, M. Siddiqi, D. Jones, J. Shute, A. Gubarev, S. Venkataraman, and D. Agrawal. Mesa: Geo-replicated, near real-time, scalable data warehousing. In PVLDB, 2014.

[27] C.-Y. Hong, S. Kandula, R. Mahajan, M. Zhang, V. Gill, M. Nanduri, and R. Wattenhofer. Achieving high utilization with software-driven wan. In SIGCOMM, 2013.
[28] K. Hsieh, A. Harlap, N. Vijaykumar, D. Konomis, G. R. Ganger, P. B. Gibbons, and O. Mutlu. Gaia: Geo-distributed machine learning approaching LAN speeds. In *NSDI*, 2017.

[29] C.-C. Hung, L. Golubchik, and M. Yu. Scheduling jobs across geo-distributed datacenters. In *SoCC*, 2015.

[30] P. Hunt, M. Konar, F. P. Junqueira, and B. Reed. Zookeeper: Wait-free coordination for internet-scale systems. In *USENIX ATC*, 2010.

[31] P. Hunt, M. Konar, F. P. Junqueira, and B. Reed. Zookeeper: Wait-free coordination for internet-scale systems. In *USENIX ATC*, 2010.

[32] P. Hunt, M. Konar, F. P. Junqueira, and B. Reed. Zookeeper: Wait-free coordination for internet-scale systems. In *USENIX ATC*, 2010.

[33] M. Isard, M. Budiu, Y. Yu, A. Birrell, and D. Fetterly. Dryad: Distributed data-parallel programs from sequential building blocks. In *EuroSys*, 2007.

[34] M. Isard, V. Prabhakaran, J. Currey, U. Wieder, K. Talwar, and A. Goldberg. Quincy: fair scheduling for distributed computing clusters. In *SOSP*, 2009.

[35] S. Jain, A. Kumar, S. Mandal, J. Ong, L. Poutievski, A. Singh, S. Venkata, J. Wanderer, J. Zhou, M. Zhu, J. Zolla, U. Hölzle, S. Stuart, and A. Vahdat. B4: Experience with a globally-deployed software defined wan. In *SIGCOMM*, 2013.

[36] V. Jalaparti, P. Bodik, I. Menache, S. Rao, K. Makarychev, and M. Caesar. Network-aware scheduling for data-parallel jobs: Plan when you can. In *SIGCOMM*, 2015.

[37] K. Kloudas, R. Rodrigues, N. M. Preguiça, and M. Mamede. PIXIDA: optimizing data parallel jobs in wide-area data analytics. In *PVLDB*, 2015.

[38] H. Lee, K. Chung, S. Chin, J. Lee, D. Lee, S. Park, and H. Yu. A resource management and fault tolerance services in grid computing. *J. Parallel Distrib. Comput.*, 65(11), 2005.

[39] Microsoft. Azure regions. https://tinyurl.com/y98skbet.

[40] A. Rabkin, M. Arye, S. Sen, V. S. Pai, and M. J. Freedman. Aggregation and degradation in jetstream: Streaming analytics in the wide area. In *NSDI*, 2014.
[53] X. Zhang, Z. Qian, S. Zhang, X. Li, X. Wang, and S. Lu. COBRA: Toward provably efficient semi-clairvoyant scheduling in data analytics systems. In INFOCOM, 2018.

[54] L. Zheng, C. Joe-Wong, C. W. Tan, M. Chiang, and X. Wang. How to bid the cloud. In SIGCOMM, 2015.