PIVOT: Cost-Aware Scheduling of Data-Intensive Applications in a Cloud-Agnostic System

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***Abstract*— We have witnessed a surge in big data applications being hosted by assorted cloud vendors, and the astronomical amount of data they produce and consume on a daily basis. Traditional cluster computing frameworks can hardly cope with the unprecedented data volume and the geo-distributed, cross-cloud data distribution due to their limited scalability and adaptability across the heterogeneous clouds. Moreover, running data-intensive applications across clouds at will is extremely cost-inefficient and likely to incur outrageous expenses. Hence, we introduce our cloud-agnostic system PIVOT with the novel *cost-aware* scheduling algorithm, which enables data-intensive applications to run and scale across clouds instantly in a cost-efficient manner. We evaluate our system and scheduling algorithm extensively with simulation, and real-world big data applications on a deployment across 11 regions on AWS and GCP. The experimental results show that PIVOT achieves over 55% saving in expense for VM subscription and up to 92% for egress network traffic compared to the state-of-the-art baselines. Notably, the *cost-aware* scheduling also achieves up to a 10x speedup in data transfers for data-intensive applications.**

I. Introduction

As the demand for cloud computing trends up, a number of cloud-based platforms have been developed in the industry and academia to address the increasing needs of data analysis and processing in the scientific and commercial sectors. As a result, valuable datasets are stored in the cloud across various geographical regions and cloud platforms. For instance, more recently the National Institute of Health (NIH) established the Commons Cloud Pilot project [15] to broaden access to high valued datasets across Amazon Web Services (AWS) and Google Cloud Platform (GCP). Similarly, the National Oceanic and Atmospheric Administration (NOAA) provide access to real-time and archival weather radar data in AWS [17] for weather data analysis and prediction. Scientists however face steep challenges to be able to use these valuable datasets in ways that will enable new research collaborations.

The distribution of data across cloud providers imposes three major challenges for data-driven analysis and applications: 1) The heterogeneity in resources, networking, APIs and runtime among clouds prevents applications from scaling out across clouds, leveraging their unique capabilities and offerings (*e.g.,* Google Genomics, SAGE) and executing close to data. In other words, a user either runs an application on one cloud or the other but not across; 2) Without the ability to scale across clouds in a seamless fashion, the applications trigger cross-region and cross-cloud data movements, which can hinder application performance due to low network throughput over the wide-area network (WAN). That is, to analyze combined data hosted in two clouds data must be moved out of one cloud into the other; 3) Since commercial clouds monetize egress network traffic, *i.e.,* traffic result from moving data outside a cloud region within or across clouds, cross-cloud data analysis can incur prohibitive monetary cost for large datasets.

Therefore, minimizing the *financial* burden that hosting data and running computation in the cloud imposes on the user is critical to promote the adoption of cloud computing. Later we quantify the implications of making compute placement decisions that are oblivious to this cost. At the heart of our research work is the development of new scheduling strategies and techniques that factor egress network traffic cost into scenarios where data is distributed across multiple clouds and/or cloud regions.

Application efficiency is one other aspect that deters scientists from migrating their data-intensive applications into cloud environments. These applications are mainly data analytic workflows consisting of processes with temporal and software dependencies on each other, which execute on geo-distributed datasets and may produce new datasets at scale. Workflow engines such as Toil [39] and Galaxy [10] are commonly used in the scientific community for data analysis. These solutions, albeit providing predictable performance in controlled campus infrastructure, have not been designed to perform well on geo-distributed environments; their scheduling capabilities are oblivious to both the network infrastructure that connects compute and storage resources as well as data locality.

To address the aforementioned challenges we propose PIVOT, a cloud agnostic framework that creates an abstraction layer over compute and storage resources distributed across cloud providers to create the illusion of one very large computer, thus hiding the complexity and heterogeneity of individual providers, services, and offerings. These resources are presented to users through a unified API via which data processing applications such as workflows can be executed and scaled across resources independently of where data is located. To achieve this, PIVOT decouples the abstraction and management of data and compute, and builds on advanced middleware mechanisms that orchestrate how these resources are utilized *jointly* to provide applications with acceptable performance, while taking into account the financial cost on behalf of the users. A fined-grained resource model for cloud topology in combination with cost-aware scheduling algorithms allows PIVOT to place computation

close to the data in order to minimize data movement and egress network traffic cost. We deployed an open-source based beta implementation of PIVOT across AWS and GCP and demonstrated its effectiveness through experiments with synthetic workloads. Our results show that by using its novel architecture and middleware mechanisms PIVOT can minimize egress network traffic cost ($> 60\%$) and improve network throughput up to a factor of 4x as compared to using traditional cost and data-locality oblivious scheduling strategies, respectively.

The key contributions of our work are manifold: (1) We have pioneered a *cloud-agnostic* framework and architecture that creates the illusion of one single large computer to users thus hiding the heterogeneity and complexity of cloud platforms. (2) We have developed middleware mechanisms that orchestrate these resources in a unified manner and enable the deployment of applications across multiple clouds without imposing additional burden on the user. (3) We have developed a scheduling algorithm aware of cost and data locality in that it discerns between cloud regions and providers to place applications close to the data, thus minimizing data movement, improving performance, and reducing financial cost. (4) We performed an empirical and simulation-based evaluation of data-intensive applications in cross-cloud environments with respect to cost and throughput. To the best of our knowledge this is a first of a kind analysis on cross-cloud environments. (5) We have developed an open-source implementation of this framework that is available to the community to deploy their own software stack.

The rest of the paper is organized as follows: we formulate the problem approached in this paper in Section II; then we briefly introduce the architecture and key components of PIVOT in Section III; the cost-aware scheduling algorithm is detailed in Section IV and extensively evaluated in Section V; we review relevant related research works in Section V; we conclude the paper and propose future works in Section VII.

II. Problem definition

Below we introduce a formal definition of the problem. We consider a workload model wherein an application consists of potentially multiple tasks, and these tasks can have dependencies which drive application-level scheduling decisions.

$$\min \quad \alpha \cdot \sum_{\eta \in H} i_\eta \cdot u_\eta \tag{1a}$$

$$+ \beta \cdot \sum_{\tau \in T} \sum_{\tau' \in T} \sum_{\eta \in H} \sum_{\eta' \in H} (P_{\tau\eta} + P_{\tau'\eta'}) \cdot e_{\eta\eta'} \tag{1b}$$

$$\text{s.t.} \quad \sum_{\tau \in T} d_{\tau k} \cdot P_{\tau\eta} \leq R_{\eta k}, \quad \forall \eta \in H, k \in K, \tag{1c}$$

$$\sum_{\eta \in H} P_{\tau\eta} = 1, \qquad \forall \tau \in T, \tag{1d}$$

$$U_\eta \in \{0,1\} \qquad \forall \eta \in H, \tag{1e}$$

$$P_{\tau\eta} \in \{0,1\} \qquad \forall \tau \in T, \forall \eta \in H \tag{1f}$$

Tasks T are placed and executed on geo-distributed virtual machine (VM) hosts H provisioned across different regions and clouds. Note that herein we use VM and host interchangeably. Each task $\tau \in T$ has a resource demand d_τ and each host $\eta \in H$ is associated with R_η amount of resources available. The vectors d_τ and R_η are 4-dimensional, representing the resource demand and capacity of CPUs, RAM, disk and GPUs, respectively. Here we use K to represent the resource dimensionalities. Following the IaaS business model in the cloud, every running host η incurs a VM subscription cost of i_η dollars per hour, and we assume VMs are turned off timely when idle. We use a bit array $u_{|H|}$ to indicate whether host η is in use. Additionally, moving data between hosts η and η' results in egress cost $e_{\eta,\eta'}$ per gigabyte. Lastly, we use a binary matrix $P_{|T|\times|H|}$to represent the placement of the tasks on the hosts. The problem is formulated as above.

The objective is to minimize the total expense for VM subscription (1a) and egress network traffic (1b). The constraint (1c) is the capacity constraint that limits the total resource demand of tasks placed on a host to the resource capacity of the host in any dimension. The constraint (1d) ensures that a task can only be placed on one host at any point of time. The constraints (1e) and (1f) indicate that U and P are binary, respectively. We recognize the problem as a variant of the **multi-dimensional vector bin packing problem (MDVPP)** [23] [28], which is proven NP-hard [28]. Hence, we propose a **cost-aware heuristic algorithm** in this paper to tackle the problem.

III. PIVOT

In PIVOT, we seek to support cross-cloud, cross-region execution of data-intensive applications while hiding the complexity of the underlying heterogeneous systems and respecting cost and performance requirements of the application. We achieve this through the introduction of a *cloud-agnostic framework* that abstracts virtual infrastructure provided by IaaS across clouds, and a versatile *two-level scheduling* approach that minimizes cost by optimizing for data locality.

A. PIVOT *Architecture*

The PIVOT architecture (Fig. 1) is designed with *cloud agnosticism* at its heart. At the bottom, we build a *cross-cloud virtual infrastructure* that enables seamless network connectivity among geo-distributed regions and clouds. On top of it, we build the *abstraction layer* that abstracts computing and storage resources and transforms them into standard units uniformly consumable by applications. Finally, a *scheduling layer* above controls task placement while considering both system-wide goals and application-level scheduling strategies.

The *cross-cloud virtual infrastructure* unifies resources provisioned in different regions and clouds in a standard fashion, creating an illusion of a single pool and orchestrating all aspects of virtual resource management and communication across cloud regions. This layer is built on top of core cloud IaaS services commonly provided by major cloud vendors including VM instances, persistent storage, virtual private cloud (VPC) and virtual private networking (VPN). In every cloud region, two types of hosts are provisioned – *computing hosts* for computation and *storage hosts* for data persistence.

The hosts are interconnected through a *supernet* spanning over all the regions and clouds. We construct the *supernet* with VPCs and VPN tunnels; there is one VPC in every region peered up with other regions using *VPC peering*; regions in different clouds are connected via VPN tunnels. Every VPC is allocated with a unique, contiguous block of private IP addresses to ensure that every host in the network is uniquely addressed. The *supernet* greatly simplifies both the communication among hosts by connecting them within the same network, and the routing among application tasks.

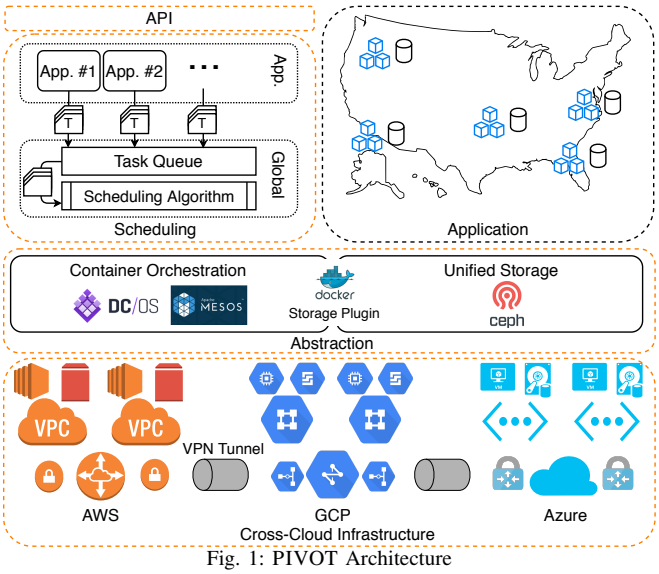


Fig. 1: PIVOT Architecture

The *abstraction layer* ensures that applications can run, scale, and access data among all the regions and clouds seamlessly. It consists of two components – *container orchestration* [8] for application deployment, configuration and provisioning, and *unified storage* for high accessibility to data. Containerization allows us to encapsulate application logic in a self-contained manner and makes applications portable among heterogeneous environments. For high accessibility to data, we deploy a unified distributed storage system across all the regions and clouds; this approach makes data and persistent storage accessible by applications anywhere in the system. Every task in an application is executed as a *container* on the *computing host*, and ingests/persists data from/to one or many persistent *volumes* located on the *storage hosts* if needed. Additionally, we have developed a *Docker volume plugin* [4] that allows *volumes* to be mounted as POSIX-compliant file systems within *containers* for easy data access. Moreover, by leveraging the *node affinity* feature available in common container orchestration [7] [14] and distributed storage [3] systems, the *abstraction layer* is able to leverage *placement hints* provided by the upper-layer components for custom placement of *containers* and *volumes* on specific hosts, availability zones (AZs), regions or clouds. This capability is critical for the *scheduling layer* to manipulate the placement of tasks and associated datasets, *e.g.,* pinning a deep learning application to a GPU-enabled host. In our prototype implementation, we adopt DC/OS (Mesos) [6] and Ceph (CephFS) [2] for container orchestration and distributed data storage, respectively. However, it is worth noting that PIVOT's architecture is generic and thus container orchestration and distributed storage implementations can be substituted by alternative technologies such as Kubernetes and GlusterFS [11], accordingly.

B. Two-level scheduling framework

To accommodate the diverse scheduling goals of applications, we devise a modular, extensible *two-level scheduling framework* that allows for custom scheduling algorithms thus following the separation-of-concerns design principle. The framework consists of a single *global scheduler* and an extensible array of *application schedulers*.

The *application scheduler* is responsible for task scheduling within an application. An *application scheduler* is typically built-in and provisioned with the application; it schedules tasks so to achieve application-level goals. For instance, for workflows the default *application scheduler* implements the classic dependency resolution algorithm that resolves dependencies among tasks. In PIVOT a custom scheduler is developed by implementing and installing the abstract *application scheduler* as a framework module. Newly installed schedulers can be extended and reused by other applications with every application running its own instance of the *scheduler*. The scheduler operates in a phased fashion; it monitors the state of tasks and queries the system-wide resource availability periodically throughout the lifetime of the application,. Scheduling decisions at the application-level are communicated to the global-scheduler for system-wide scheduling considerations. The *global scheduler* has a built-in *task queue* where tasks submitted by the *application schedulers* are queued for scheduling and final dispatching. The *global scheduler* also runs periodically, invoking the global scheduling algorithm to schedule tasks in the *task queue* and then clearing the queue at each phase. The scheduling algorithm makes placement and resource allocation decisions based on the task specifications and the resources available in the system. The scheduled *containerized* tasks are sent to the container orchestrator in the *abstraction layer* for provisioning, configuration, and execution. When the minimum requirements of a task cannot be fulfilled due to issues like resource shortage, it is put back into the *task queue* for the next scheduling iteration and the *global scheduler* increments a counter of scheduling failures for the task. Once the counter has reached a configurable threshold, the *global scheduler* notifies the corresponding *application scheduler* to handle the scheduling failure.

Our proposed two-level design of the scheduling framework enhances the versatility of the *scheduling layer* by enabling the offloading of application-specific scheduling logic to the upper-level scheduler.

IV. Cost-Aware Scheduling Algorithm

Recall that we are concerned with lowering the financial barrier resulting from high egress expenses incurred by moving data in/out cloud regions while improving application efficiency. To strike a balance between both factors we propose a *cost-aware scheduling heuristic* which aims at **saving cloud expenditures** for geo-distributed applications running on PIVOT while **improving data transfer efficiency** in a

best-effort manner. We implement our algorithm as a *global scheduler* in PIVOT.

A. Algorithm design

As identified in Section II, cloud expenditures are mainly comprised of expenses for *VM subscription* and *egress network traffic*, caused primarily by host **resource underutilization** and excessive **egress data transfers**. Furthermore, since network bandwidth is typically constrained among regions and clouds, egress data transfers tend to exhibit low efficiency and high delay. Ideally, consolidation of tasks into the least number of hosts and egress data transfers can both avoid unnecessary expenses and improve efficiency.

We realize that the problem of task consolidation is analogous to the known **vector bin packing (VBP)** problem, in which the tasks and hosts are *items* and *bins*, respectively. Greedy approximation algorithms such as first-fit (FF) [33], best-fit (BF) [20], and their variants, are proven effective in approximating the optimum for the problem. We refer to the family of FF and BF algorithms as VBP algorithms. We refer the reader to [26] [33] for an in-depth analysis of VBP algorithms.

However, whereas the bins in the classic VBP problem are presumably homogeneous, hosts in PIVOT are distinguished by **egress cost**, **network bandwidth** and **data locality**. More specifically, it is preferable for a task to be placed on a host with its input data for data locality, which we refer to as the *anchor*. If the *anchor* is unavailable, another host is selected based on a function of its egress cost and available network bandwidth to the *anchor*. Intuitively, hosts with lower egress cost and higher bandwidth are preferred for potentially better cost saving and data transfer efficiency.

Following this analysis, we design our *cost-aware scheduling algorithm* as follows (Fig. 2): 1) the initial VBP problem is divided into sub-problems based on the data locality requirements of the tasks; 2) an *anchor* is selected for every sub-problem, while tasks and hosts are sorted *w.r.t.* the selected *anchor*; 3) the classic FF algorithm is used to pack tasks into the prioritized hosts. In the rest of this section, we describe each step in detail.

```
Func schedule(T, H):
1   G ← groupTasks(T)
2   for g ∈ G do
3       g ←sortTasks(g)
4       hosts ←sortHosts(H, θ)
5       FirstFit(g, H)
6   return tasks
```

Fig. 2: Cost-aware scheduling

B. Task grouping and data locality inference

The first step is to divide the problem based on data locality requirements. In effect, tasks are grouped by their *anchors*. Note that although PIVOT allows users to provide fine-grained data placement information, such information is seldom available and has to be inferred to retain data locality. We adopt a **data locality inference** approach to deduce data locality requirements from implicit observations in task specifications. We leverage two pieces of information – the *application locality* and *dependencies* encoded in application specifications. Intuitively, we assume tasks of the same application are likely to share data among each other due to the inter-operations and communications. Furthermore, co-dependent tasks, *e.g.,* workflows, tend to ingest data from tasks upstream since they may use the output data of the precedent tasks as input data. Hence, it is intuitive to co-locate tasks with their peer (application-locality) or precedent (dependencies) tasks for data locality. As we show later in Section V this measure has a significant impact on data-intensive applications such as workflows.

```
Func groupTasks(T):
1   G ← {}, θ ← ∅
2   for τ ∈ T do
3       if τ.dataPlacement ≠ ∅ then
4           θ ← τ.dataPlacement
        else if τ.dependencies ≠ ∅ then
5           θ ← Host η where most of τ's predecessors are placed
        else if τ.application has the anchor set then
6           θ ← Anchor of τ.application
        else
7           θ ← Random host
8           Set θ as the anchor of τ.application
9       g_θ ← g_θ ∪ {τ}, G ← G ∪ {g_θ}
10  return G
```

Fig. 3: Task grouping

Fig. 3 illustrates the steps of *task grouping*. First, tasks with explicit information about placement of input data use the location of input data as the *anchor* (Line 4); tasks with dependencies select the host wherein most predecessors are placed as the *anchor*. Following, tasks are grouped by their *anchor* (Line 9). Tasks without an *anchor* are grouped based on the application they belong to and each such group is assigned a random *anchor* (Line 7-8) to ensure the peer tasks are co-located to meet application-locality requirements.

C. Task ordering

For each group formed in the previous step, the algorithm sorts the tasks in decreasing order of their resource demand [26] which consequently results in *lower VM subscription cost* for the user.

To sort the tasks, we model the resource demand of each task *geometrically* as an *Euclidean vector* and calculate its L_2-norm ($||d_\tau||_2$) as the *size* of the task. We note that this is considered one of the most effective geometric approaches in the realm of VBP problems [33].

D. Host ordering

The host ordering is critical since it captures important distinctions among hosts that have measurable impact on the quality of the scheduling decisions. We introduce a *host scoring function* as below to facilitate the host ordering quantitatively.

$$Score(\eta, \theta) = \frac{||R_\eta||_2 \cdot (b_{\eta\theta} + b_{\theta\eta})}{C_{\eta\theta} + C_{\theta\eta} + \epsilon}$$

We factor in bidirectional network bandwidth (b) and egress cost (C) between the host η and the *anchor* (θ) – the score is positively correlated with the network bandwidth but negatively with the egress cost. Likewise, we model the resource capacity on host η (R_η) as a 4-dimensional Euclidean vector and use its length as the host *capacity*, which is also positively correlated with the host score. The

hosts are sorted in the decreasing order of the host score given by the function. Effectively, the algorithm prioritizes hosts with larger *capacity*, more abundant bandwidth but less egress cost from/to the *anchor* for task placement.

In practice, we estimate the network bandwidth regularly using *Assolo* [29] – a non-intrusive bandwidth estimation tool. It imposes limited impact on running applications and greatly saves the egress cost for bandwidth measurements as compared to most intrusive alternatives (*e.g.,* `iperf` [13]).

E. Vector bin packing

To pack tasks into the sorted hosts we use the classic *FF algorithm*. By design, the algorithm attempts to place each task onto the first host it can fit in (first-fit), and only consider the next host (open a new *bin*) when no fit is found. With the sorted host array, tasks are packed onto high-score hosts first and proceed in decreasing order of the host score.

V. Evaluation

To evaluate the effectiveness and feasibility of our approach in PIVOT, we deploy PIVOT across AWS and GCP clouds. We drive the experiments using both simulations and real applications to investigate the system and proposed algorithm in depth. For performance metrics, we focus on the cost savings in VM subscription and egress network traffic, but also observe the efficiency of application executions and data transfers.

A. Experiment setup

1) PIVOT *deployment:* PIVOT is deployed across 31 AZs in the 11 North America regions[1] on AWS and GCP. The hosts provisioned in the deployment are uniform in capacity among the regions, each *computing host* having 4 Skylake CPUs, 8GB RAM and 150GB disk space (*c5.xlarge* and alike instance/machine type) and each *storage host* having 2 CPUs, 4GB RAM and 150GB disk space (*c5.large* and alike). The total number of hosts ranges between $100 - 200$, and the number in each AZ varies between $1 - 8$.

2) Simulation environment: The simulator simulates the exact cross-cloud, geo-distributed topology of the real deployment. We collect the network trace among the regions and clouds using `iperf3` for accuracy. Different from the real deployment, we simulate *p3.8xlarge* hosts (32 CPUs, 244GB RAM, 320GB disk and 4 GPUs) to evaluate the algorithms with increased resource capacity and dimensionalities. The simulator is developed in Python using Simpy [18] and available at [16].

3) Workload: In the simulation, we evaluate the algorithm against data-intensive workflows. We randomly generate workflows with a mix of common communication patterns [38] including *sequence*, *parallel-split* and *synchronization*. Each task ingests 10MB$-$1GB data from its predecessors, if any. The level of task parallelism for each workflow ranges between $1-100$ tasks; there are over $5,000$ tasks concurrently running system-wide.

[1] `us-east-1`, `us-east-2`, `us-west-1`, `us-west-2`, `ca-central-1` on AWS, and `us-east1`, `us-east4`, `us-west1`, `us-west2`, `us-central1`, `northamerica-northeast1` on GCP

We also introduce two featured, real-world use cases - 1) a Hail [12] distributed application and 2) the TOPMed alignment workflow encoded in Common Workflow Language (CWL) [19]. The reasoning behind these choices is that both workloads exhibit high-level of compute parallelism and data dependencies thus stressing the challenges encountered in the cloud distributed environments we consider in this work. The Hail is a popular open-source genomic analytical tool developed by the Broad Institute which builds on Spark [1] to enable large-scale genomic analysis; the TOPMed alignment workflow is an example of CWL workflows publicly available at [9]. We have ported both Hail cluster and CWL workflows as applications runnable on PIVOT to serve the biomedical community and enable them to take advantage of the cross-cloud scalability.

The TOPMed genome sequence alignment pipeline adapted for this experiment is available at [5]. The number of parallel tasks varied between 10-70. The topology of the dependency graph is a *map* and *reduce* structure starting with splitting the input, two intermediate phases processing the chunks, and a final aggregation phase. The high level of parallelism and data dependencies lends itself well to analysis of distributed scheduling algorithms.

4) Baseline: In our evaluation we compare our cost-aware to the following baseline algorithms.

- `Opportunistic` is a common scheduling strategy that assigns tasks to hosts with sufficient resources *opportunistically* for high resource utilization in overall as adopted in [30] [22] [40]. In our implementation, the scheduler assigns tasks randomly to the hosts where they can fit in.
- `VBP` consists of the FF and BF family of algorithms.
- `Mesos` [30] uses a *resource offer* mechanism that achieves high data locality and scalability within the data center. It is a more sophisticated *opportunistic* algorithm than the `Opportunistic`. In the evaluation, we compared our algorithm to `Mesos` with real applications.

B. Results

We first present the experimental results of the simulation. Fig. 4 compares our algorithm to the baseline algorithms across several aspects. As shown in the figure, the `Opportunistic` strategy performs the worst in cost efficiency since it does neither task packing nor own the awareness of egress cost. This follows intuition since this scheduling strategy tends to spread out tasks randomly across regions thus fragmenting resource utilization on the hosts and leading to high cost in host subscription and egress fees. In contrast, the `cost-aware` strategy saves up to 55.2% and 89.3% of the host subscription and egress cost as compared to the `Opportunistic`, respectively. Although saving comparably 53.3% in host subscription cost due to the effective consolidation of tasks into a few hosts as indicated in the figure, the `VBP` only reduces 13.5% of the egress cost. This is mainly because `VBP` is oblivious to data locality and the egress cost model, it scales out applications across cloud regions thus causing excessive cost in egress

network traffic. In comparison, by grouping tasks and ordering hosts respecting data locality, the `cost-aware` is able to schedule tasks in proximity to their input data and *radially* scales out applications centered around their *anchor*. Effectively, the algorithm favors cost-efficient hosts when placing applications and therefore achieves the greatest cost saving. As a consequence of the high levels of data-locality achieved by the algorithm, the `cost-aware` incurs the least delay due to data transmission and network congestion.

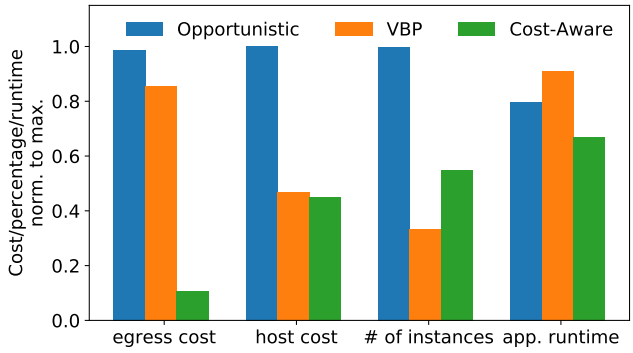


Fig. 4: Comparison of egress cost, host subscription cost, average number of hosts used and application runtime. `cost-aware` saves up to 55.2% and 89.3% of the cost for host subscription and egress traffic.

Interestingly, we observe the `cost-aware` also achieves the least average application runtime as compared to the baseline strategies. After careful analysis of the simulation data, we find that the runtime improvement is mostly due to reduced data transfer time. As illustrated in Fig. 5, the `cost-aware` saves up to 90.4% of the data transfer time per task. Notably, `VBP` performs the worst due to the significant delay caused by network congestion, which represents 47.2% of the data transfer time. This result highlights the importance of taking into account the network bandwidth for making scheduling decisions in distributed cloud environments. More specifically, by virtue of its network obliviousness the `VBP` places tasks onto hosts with bandwidth-limited network paths to their *anchor* and introduces data transmission delays. To make things worse, the task packing tends to create *hot spots*, where excessive network exacerbates congested paths. We also notice that the `VBP` results in higher host subscription cost although it consolidates tasks into fewer hosts than `cost-aware`. This is mainly due to the slow data transfers greatly prolonging the host provisioned time when using `VBP`.

Since the bandwidth factor outweighs other factors in the host scoring function, the `cost-aware` algorithm is able to avoid the congestion dynamically and trade financial cost for load balancing in the long run.

Fig. 6 shows total cost as a function of number of applications concurrently running in PIVOT. As observed, when the system is lightly loaded, *i.e.,* $10-100$ applications, the `cost-aware` avoids egress cost by containing limiting the footprint of an application within a cloud region. As the number of applications increases, we observe that all the algorithms scale out the applications by placing tasks across multiple regions as reflected in the increasing cost for host subscription and egress traffic. Nevertheless, with the `cost-aware` strategy the egress cost increases at a much

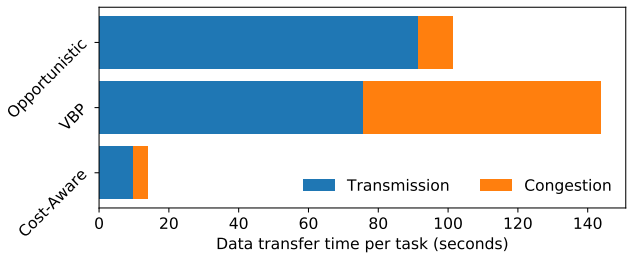


Fig. 5: Average data transfer time per task. `cost-aware` saves up to 90.4% of data transfer time due to strategic selection of fast network path and avoidance of network congestion.

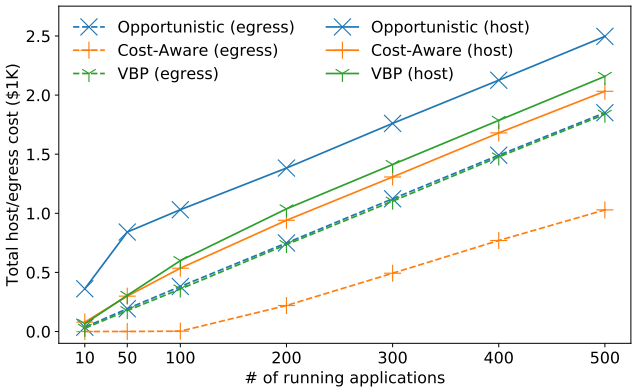


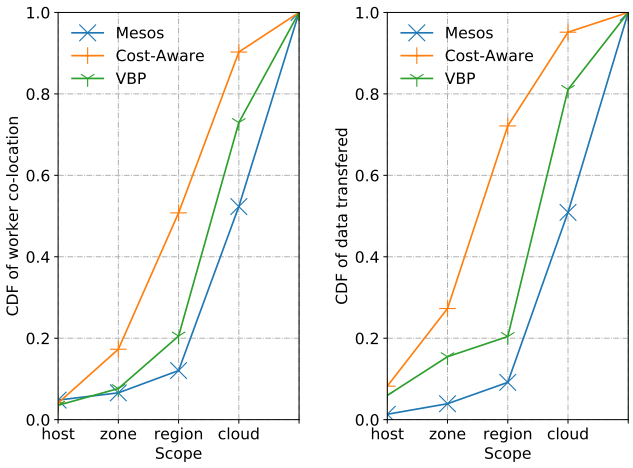
Fig. 6: Variation of cloud expenses with increasing number of concurrently running applications. Despite the lowest egress and host subscription cost, `cost-aware` achieves mildest cost increase as applications scale up lower rate as compared to the baseline algorithms.

1) The Hail cluster: A Spark cluster consists of a set of *worker processes* (workers) that execute data processing jobs. In PIVOT, Hail *workers* are considered long-running tasks in our workload model. The management of the Hail workload is managed by the Spark framework and therefore is completely *opaque* to PIVOT. Therefore, our cost-aware algorithm only takes into account information about the application locality, *i.e.,* all Hail tasks (workers) are grouped, when making scheduling decisions. To compare the effectiveness of our algorithm against `VBP` and `Mesos` we launch Hail clusters with $10-100$ *workers*; following we discuss the results of this experiment.

Fig. 7a illustrates the placement distribution of *workers* for Hail clusters of varying sizes. As observed, the `cost-aware` algorithm co-locates the majority of the *workers* within the same region and cloud (50.8% and 90.3%, respectively).

Additionally, in Fig. 8 we show a cost-throughput trade off analysis for all three scheduling algorithms. Notice that the origin of the graph represents the optimum point at which data transfers can be completed instantly without any monetary cost, and every point represents the average data transfer throughput and egress cost for a Hail cluster instance. As observed, most scheduling decisions under the `cost-aware` algorithm are close to the optimum while those under `Mesos` and `VBP` are concentrated on the top right corner of the graph. This follows intuition since by co-locating *workers* the `cost-aware` algorithm improves data locality (as reflected in throughput) and reduces egress cost. This is in contrast to the low throughput resulting

from the sparse distribution of *workers* when using `Mesos` and `VBP`. Note the outlier placement decisions landing at the far top right corner under the `cost-aware` scheduler. These outliers reveal the limitation of application-locality-based scheduling in that application-locality does not imply data-locality in a distributed system (an assertion valid in centralized environments, *e.g.,* single node). We argue that considering the limited information provided by the application to the scheduler, the `cost-aware` strikes a good trade-off between cost and data locality improvement.



(a) Hail cluster (b) CWL workflow

Fig. 7: CDF of worker co-locations/data transferred for Hail clusters/CWL workflows in different scopes, respectively. `cost-aware` effectively co-locates the *workers*/tasks for improved data locality and less egress cost.

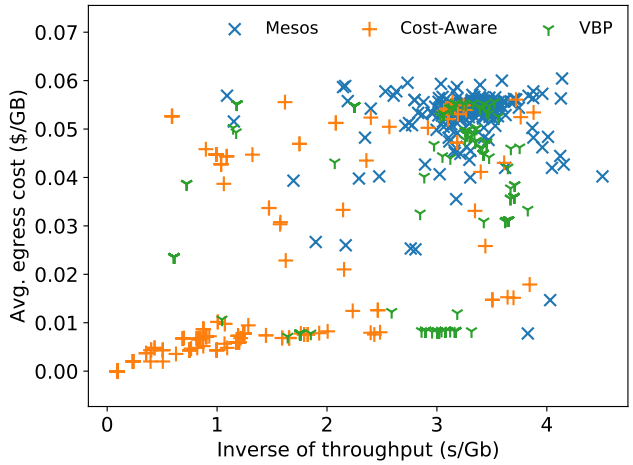


Fig. 8: Footprints of the Hail cluster deployments in the *cost-throughput* space. Most deployments by `cost-aware` are clustered in proximity to the optimum, while those by the baselines mostly distributed at the far end.

2) CWL workflows: CWL workflows are representative of the applications considered in our earlier simulation analysis. More specifically, data dependencies among workflow jobs are defined in the CWL workflow specification – described as input and output files for each step of the workflow. Thus, the scheduling algorithm can take advantage of this additional information to infer data locality accurately when making placement decisions.

In Fig. 7b we notice that the locality of interdependent tasks which read their input data from a preceding task increases significantly under the *cost-aware* scheduler. A more detailed analysis of our results shows that once the anchor tasks are placed, the scheduling strategy makes a best effort to balance locality and performance as reflected by the *clustering* of descendent tasks.

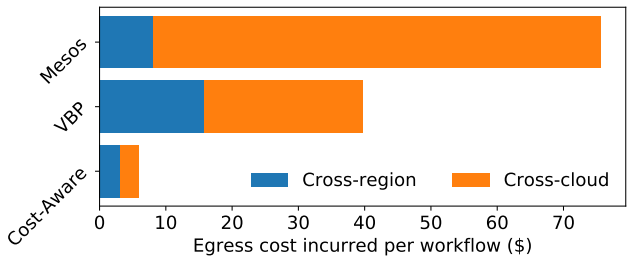


Fig. 9: Average egress cost incurred by running the CWL workflows. `cost-aware` saves up to $2,092 (92.2%) in total for 30 workflow runs.

Recall that cross-region cost is significant, therefore we are concerned with keeping data transfers within cloud regions. Note that in Fig. 7b, 9.1%, 20.4%, and 72.1% of data transfers were kept within a region using the `Mesos`, `VBP`, and `cost-aware` schedulers, respectively. The steep CDF slope of the `cost-aware` strategy demonstrates the effectiveness of our algorithm; only 4.9% of transfers span clouds compared to 18.9% and 49.0% for `VBP` and `Mesos`, respectively. Turning to Fig. 9 we see a drastic reduction in egress charges, and a shift from charges mostly being from cross-cloud in `Mesos` (89.2%) and `VBP` (60.2%), to charges being mostly from cross-region within a cloud in `cost-aware` (53.4%).

VI. Related Work

VM and container packing. VM packing is a well-studied problem [20] [21] [33] that aims at packing VMs into the least number of physical machines. The problem is generalized as a MDVPP problem and a family of FF- [33] and BF-based [21] heuristics have been developed and thoroughly studied. [33] provides a comprehensive summary of heuristics for the problem. More recently, the packing approaches are extended to applications such as data streaming [34] for optimal operator placement in the cluster. With the emergence of containers and their adoption in the cloud, there is a rising interest in packing containers into the least number of VMs to minimize VM subscription cost, which is analogous with VM packing. Stratus [24] has developed a cost-aware container scheduler that minimizes the VM instance hour and the associated cost in the cloud. These works partially share the same objective with ours and provide intuitions for our algorithm. However, we extend them into a cross-cloud context and investigate the impact of egress cost within and across clouds, which is unique in this context. Our evaluation also demonstrates that it is sub-optimal to directly apply existing VBP solutions in the cross-cloud context due to the absence of cost awareness.

Geo-distributed data locality. Recent works recognize the increasing importance of data locality in the context of geo-distributed computing and data analytics [32] [25] [31] [35]. Awan [32] develops a locality-aware scheduler for geo-distributed data-intensive applications leveraging the explicit task runtime and data placement. DRASH [25] and Cachalot [31] dynamically replicate and cache commonly

used data across geo-distributed resources to enhance data locality.

Cloud agnosticism. Only a few research works explore the cloud-agnostic and multi-cloud solutions for running distributed applications, and most of them were done prior to the widespread adoption of container technologies, which drastically change the landscape of cloud agnosticism. [27] classifies a stack of cloud solutions for easing the heterogeneity and enhancing inter-operability among clouds. [36] and [37] develop multi-cloud storage systems with bandwidth and cost efficiency in mind. PIVOT addresses all aspects of resource abstraction in a holistic manner.

VII. Conclusion and Future Works

We introduce PIVOT as a holistic cloud-agnostic system, which enables seamless execution and scaling of data-intensive applications across geo-distributed regions and clouds. More importantly, we develop an innovative cost-aware scheduling algorithm that effectively reduces up to 55% and nearly 92% of VM subscription and egress cost for applications running across clouds, respectively. Particularly, with the data locality inference approach adopted in the algorithm, the algorithm effectively enhances the data locality and achieves up to 10x speedup in data transfers.

We look forward to exploring the possibility of introducing spot/preemptive VMs into the system to further reduce the VM subscription cost. We are also interested in adoption of distributed caching in PIVOT in order to improve locality of commonly used data and save additional egress cost.

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