Yosemite: Efficient Scheduling of Weighted Coflows in Data Centers

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Abstract—Nowadays, low latency and high throughput are required by data center applications. Coflow has been proposed as a new abstraction to capture the communication patterns in a rich set of data parallel applications, so that their application-level semantics can be effectively modeled. By taking coflows, instead of flows or packets, as the basic elements in network resource allocation or scheduling, application-level optimization goals such as reducing the coflow completion time (CCT) or application transfer latency can be better achieved. Although efficient coflow scheduling methods have been studied in this aspect, in this paper, we propose *weighted coflows* as a further step in this direction, where weights are used to express the importance or priorities of different coflows or applications, and weighted coflow completion time (WCCT) is set as the optimization target. We design and implement Yosemite, a system that aims to minimize WCCT by dynamically scheduling coflows according to their weights and the instantaneous network condition. We test Yosemite's performance against several flow or coflow scheduling methods, by trace-driven simulations as well as real delopyment in a cloud testbed. Our trace-driven simulations show that, Yosemite's online scheduling algorithm performs about 20%-50% and 30%-60% better than that of Varys and Aalo, two state-of-the-art coflow scheduling systems, respectively. And in our testbed evaluations, Yosemite respectively achieves 30% and 35% average improvement against Varys and Aalo.

I. INTRODUCTION

Data center is now used as the infrastructure of many applications, including file storage [24] [17], map-reduce [16], etc. These applications need the data center network to provide them with low latency and high throughput [22] [23] [27]. However, due to the limited resources, data center network can not satisfy the demands of every application. In order to use the limited network resources effectively, many schedule methods are proposed.

Flow level scheduling methods such as PDQ [19] and pFabric [10] implement SJF to let short flows preempt the bandwidth of long ones. As a result, average flow completion time will decrease. Although, flow level scheduling methods can optimize the latency of applications, it has some deficiencies [14]. On one hand, flow level optimization can lead to some tardy flows lagging the performance of the whole application because applications have dozens of flows, the communication stage cannot finish until all flows of the applications have completed. On the other hand, flow level scheduling is so frequent that it can exert huge pressure to centralized scheduler, which need to compute the schedule results as fast as possible.

To overcome the deficiencies of flow level optimization. The recently proposed network abstraction coflow regards the semantic-similar flows as a whole. A coflow is a collection of flows that share a common performance goal, e.g., minimizing the completion time of the latest flow or ensuring that flows meet a common deadline [12]. Under this abstraction, flows belonging to the same set have the same priority. This abstraction takes the characters of applications into consideration. Varys [15] incorporates network bottleneck into coflow scheduling. It uses SEBF which is also known as Smallest-Effective-Bottleneck-First heuristic to decide the scheduling sequence of coflows and use Minimum-Allocation-for-Desired-Duration (MADD) to compute the bandwidth that coflows deserve to get. It is clairvoyant method whose scheduler should know coflows' width and size of each flow beforehand. Then some schedule method such as Aalo [13], sunflows [20] and CODA [35] are Non-Clairvoyant method, they do not assume anything about a coflow's characteristics like the number of flows, endpoints, or waves, the size of each flow, flow arrival times. Their schedule methods use less coflow characters than Varys but have relatively worse performance.

We find that both the clairvoyant and the Non-Clairvoyant methods emphasize on minimizing coflow completion time [15] [20] [13]. Scheduling sequence of coflows is mainly decided by network condition with some characters such as coflow length and coflow width. However, applications in data center have different level of importance, scheduling just depends on network condition as well as the physical property of coflows is not enough. For example, assume both hadoop and erasure code storage system running in one data center, they compete for network resources. Using Varys or Aalo, bandwidth scheduling is based on network condition and coflow itself, but ignores the contents of applications. However, from the semantic of applications, computation applications may be more emergency than storage and we want them to transfer as quickly as possible. In this case, we should give higher priority to computation applications over storage applications and take the priority into consideration when scheduling.

In this paper, we use weight to quantify the importance of applications. Coflows belonging to more important applications will have larger weight. As a result, bandwidth allocation is decided by network condition, physical characters of coflows as well as the applications' importance . Our goal is to minimize average coflow weight completion time. To achieve this, in the following of this paper, we first proposal weight coflow completion time optimization(WCCO) problem. Then we introduce a 2-approximate offline algorithm [26] and change the algorithm to online version. After this, we

introduce Yosemite - a coflow scheduling system that aims to minimize average coflow completion time. Following the introduction of Yosemite system, we test the performance of it by trace-driven simulation and test-bed evaluation. Experiments show Yosemite can reduce average coflow weight completion time significantly. On average, trace-driven simulation shows Yosemite can improve about 20%∼50% of performance over Varys and 30%∼60% over Aalo. We also deploy Yosemite system on our cloud platform and run file distribute and file backup applications, test-bed experiments show that Yosemite performs about 30% and 35% better than Varys and Aalo respectively. Thus the contribution we make in this paper:

- We proposal the weight coflow completion time optimization (WCCO) problem and prove its equivalent to minimizing average job weight completion time.
- We proposal an online algorithm to minimize average coflow weight completion time and evaluate it both in simulation and on our cloud platform.
- We compare the performance of Yosemite with state-of-art coflow strategy such as Varys, Aalo and Barrat, etc.

The rest of the paper is organized as follows. In section II we introduce some background and related work. Then at section III, we define the WCCO problem and prove its equivalent to concurrent open shop problem. At section IV, we proposal Yosemite-online algorithm to schedule coflows and compare its performance with the 2-approximate offline algorithm. Section V shows the design of Yosemite system. After this, at section VI, we demonstrate the performance of Yosemite and compare it with the state-of-art coflow schedule methods. At last, section VII concludes the paper.

II. BACKGROUND AND RELATED WORK

Data center is now becoming an important infrastructure in data center network. Application needs data center to provide them with high throughput and low latency. However, resources in data center are limited, so efficiently scheduling in data center is necessary. Coflow scheduling methods can date back to flow scheduling.

DCTCP [9], D2TCP [33],L2DCT [28] and LPD [36] emphasize on flow level rate control. They propose to mark packets on a switch when instantaneous queue length exceeds a certain threshold k. The endpoints then estimate the extent of congestion by the marked packets, and throttle flow rates in proportion to that extent. With the help of ECN marking mechanism, they reduce the queue length on switches, and can reduce the queueing delay. TCP-based methods are simple, however they are implicit rate control method [10] and can never precisely estimate the right flow rates to use so as to schedule flows to minimize FCT while ensuring that the network is fully utilized. Then explicit methods are proposed.

D3 [34] and PDQ [19] can schedule flows based on some notion of urgency. They compute flow bandwidth according to flow deadline as well as network condition. A centralized controller which collects the network condition is needed. Although these methods can assign rates according to flow deadlines or flows' estimated completion time, they can not satisfy the demands of applications well. This is because distributed applications always have many parallel flows and often an application's communication stage cannot finish until all its flows have completed. If we only focus on single flow scheduling, some tardy flows may finish late and it doesn't make any sense to allocate much bandwidth to the application. As a result, scheduling applications' flows as a whole is meaningful.

Until this, both the implicit and explicit methods are all flow-level optimization methods. Having recognized limitation of flow-level methods, application level schedule methods occur. Barrat [18] schedules tasks in FIFO order but avoids head-of-line blocking by dynamically changing the level of multiplexing in the network. Using Barrat, each task has a globally unique priority-all flows within the task use this priority, irrespective of when these flows start or which part of the network they traverse. Barrat is simple, but for some large coflow, it can down many smaller ones. Varys [15] regards applications' parallel flows as coflow and it uses SEBF to schedule coflows and MADD to perform rate control, as a result, other coexisting coflows can make progress and the average CCT decreases. Varys is a Clairvoyant schedule method, which means some coflow information such as coflow length and coflow width should be known beforehand. Unfortunately, in many cases, coflow characteristics are unknown a priori and this will limit the its utilization. To overcome this, some non-Clairvoyant methods like Aalo [25] ,sunflows [20], D-CLAS [13] and CODA [35] do not need to know coflow information beforehand. They use information accumulation or machine learning to "guess" the characters of coflow. Non-Clairvoyant methods can be used more widely, however, their performance is not as good as the Clairvoyant ones such as Varys. Although coflow level scheduling methods such as Varys and Aalo perform well on reducing application transfer latency, they ignore different applications always have different level of importance and just scheduling depends on network condition and characters of coflows such as coflow length as well as width is not enough. In reality, the importance of applications should also be taken into consideration.

Some theory paper such as [29] sets weight to coflow to minimize average coflow weight completion time. We think this is good direction, however, methods such as [29] should solve complex equations and it is too complex to use in practice.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this part, we define Weight Coflow Completion Optimization (WCCO) problem and try to prove its equivalent to the concurrent open shop problem [31].

A. Data center non-blocking model

Recent researches [13] [20] [15] [10] regard the data center network as a big giant non-blocking switch which interconnects all the machines. In this model all ports have the same normalized unit capacity, and bandwidth compete bandwidth at ingresses or egresses. Such an abstraction is reasonable and matches with recent full bisection bandwidth topologies

widely used in current production data centers- To provide uniform high capacity as well as other targets like equidistant endpoints with network core, unlimited workload mobility, etc., today's production data center networks widely adopt non-blocking Clos topologies by design [25].

B. Why we choose weight

Applications in data center have to contend with each others for the limited network resources. The state-of-art schedule methods regard applications' flow set as a whole to reduce the transfer latency of applications. However, applications in data center have different level of importance, scheduling just depends on network condition as well as the physical property of coflows is not enough. We have to differentiate applications to satisfy their demand of bandwidth. As a result, how to distinguish the demands of applications is becoming an important problem.

Some previous study [33] [34] [36] use deadline to present the emergency of applications, applications have different deadlines, thus bandwidth. Deadline-aware methods aim to let applications finish before a particular time point. However, in reality, applications just need to transfer as quickly as possible rather than finishing before the time constraint. For the example of hadoop and erasure code storage system running in one data center to compete for network resources If we assume hadoop is more important than storage, we can give computation application higher priority to guarantee it to transfer as quickly as possible. In this case, setting deadline to applications is not a good choice, as applications do not have the expectation of finishing moment. We use weight to present the importance of applications, different applications have different level of importance. As a result, instead of minimizing average coflow completion time, we try to minimize average weight completion time.

C. Problem formulation

We consider the offline scheduling of n coflows on a non-blocking DCN with m hosts, i.e., there are m ingresses and m egresses, and their capacity is 1. All coflows arrive at time 0. The k-th coflow indicated by $F^{(k)}$ is a collection of parallel flows. $F^{(k)} = \{f_{i,j}^k | 1 \leq i \leq m, 1 \leq j \leq m\}$, where $f_{i,j}^k$ is the flow size sends from host i to host j. In reality, there are no flows sending from host i to host j. Under this condition $f_{i,j}^k = 0$. C_k denotes the completion time coflow $F^{(k)}$. Weight of coflow $F^{(k)}$ is w_k. We now define the Weight Coflow Completion Optimization (WCCO) problem as follows:

$$\text{minimize} \quad \sum_{k=1}^{n} w_k C_k \quad (1)$$

$$\text{s.t.} \quad \forall k, j : \sum_{\forall l: C_l \leq C_k} \sum_{i=1}^{m} f_{i,j}^{(l)} \leq C_k \quad (2)$$

$$\forall k, i : \sum_{\forall l: C_l \leq C_k} \sum_{j=1}^{m} f_{i,j}^{(l)} \leq C_k \quad (3)$$

For a given set of coflows, labeled 1...n, minimizing their average weight completion time is equivalent to minimizing their sum of weight completion time, just as (1) shown. (2) is the constraint on sender side and (3) is the constraint on receiver side.

D. NP-hard proof

In this section, we prove that the target of minimizing average coflow weight completion time is equivalent to the problem that minimizing average job weight completion time in concurrent open shop problem.

proposition *1:* Weight Coflow Completion Optimization (WCCO) problem is equivalent to the problem of minimizing the sum of job weight completion times in a concurrent open shop.

Proof: For the $m \times m$ network fabric, we mark ingress ports as $1..m$ and egress ports as $m + 1...2m$. We consider the transferring time of coflow $F^{(k)}$ through port p:

$$T_p^{(k)} = \begin{cases} \sum_{j=1}^{m} f_{i,j}^{(k)} & 1 \leq p \leq m \\ \sum_{i=1}^{m} f_{i,j}^{(k)} & m < p \leq 2m \end{cases} \quad (4)$$

As a result, for the given coflow $F^{(k)}$, there are 2m transfer subflows and each transfer time is computed as (4). Now, we consider the concurrent open shop scheduling problem with 2m identical machines (hence the same capacity). n jobs arrive at time 0 and each job has 2m types of operations on the 2m identical machines. Then each coflow can be regarded as a job and each port can be regarded as one machine. Coflow k transfers through port p is the same as job j operates on machine m. The two problems are equivalent. ∎

It has been proved that minimizing average job weight completion time is a NP-hard problem [26] [11] [31] [30], so even the offline problem WCCO is also NP-hard.

IV. ALGORITHM DESIGN AND ANALYSIS

Minimizing average coflow weight completion is indeed to find a permutation of coflows. It is NP-hard just as the proof of last section, so efficient heuristic is needed. To solve this, we first change a 2-approximate algorithm that aims to minimize average job weight completion time to coflow scheduling. Then we proposal an on-line algorithm based on this. Last of the section, we test the performance loss of the online algorithm.

A. Weight coflow completion time offline algorithm

Currently, the best known results for minimizing average job weight completion time is a 2-approximation greedy algorithm [21] [26]. The algorithm intends to minimize average job weight completion time and we can't put the original algorithm into coflow scheduling directly. According to the correspondence between WCCO and minimizing average job weight completion time problem that is introduced at section III-D, we get the 2-approximate algorithm for WCCO as Algorithm 1 shown.

Input of Algorithm 1 is $\mathcal{C}$ and $f_{i,j}$, where $\mathcal{C}$ is the coflow set and $f_{i,j}^k$ is the size of data from port i to j. Output of the Algorithm 1 is γ, which indicates scheduling permutation

Algorithm 1 2-approximation offline algorithm

Input: Coflow set $\mathcal{C}$; flow size $f_{i,j}$ from port i to port j, where $1 \leqslant i \leqslant m, 1 \leqslant j \leqslant m$

Output: γ

1: $\gamma : \{1, 2, ...n\} \leftarrow \mathcal{C}$
$UC \leftarrow \{1, 2, 3...n\}$
$P \leftarrow \{1, 2, 3...2m\}$
$W\{1, 2, ...n\} \leftarrow \{w_1, w_2, w_3...w_n\}$
2: $L_i^{(k)} = \sum_{j=1}^{m} f_{i,j}^{(k)}$
3: $L_{j+m}^{(k)} = \sum_{i=1}^{m} f_{i,j}^{(k)}$ for all k $\in \mathcal{C}$ and j $\leq$ m
4: $L_i = \sum_{k \in \mathcal{C}} L_i^k$ for all i $\in$ P
5: **for** i $\in \{n, n-1, n-2...1\}$ **do**
6: $\quad$ u=$\arg \max_{k \in \mathcal{C}} L_k$
7: $\quad \gamma[i]$=$\arg \min_{F \in UC} W[F]/L_u^{(F)}$
8: $\quad \theta = W[\gamma[i]]/L_u^{\gamma[i]}$
9: $\quad$ W[j]=W[j]-θ*$L_u^{(j)}$ for all j $\in UC$
10: $\quad L_j = L_j - L_j^{\gamma[i]}$ for all j $\in$ P
11: $\quad UC = UC \setminus \{\gamma[i]\}$
12: **end for**

of coflows. For the detail of algorithm. Line1 does some initialism operations, where UC is the set of coflows to be scheduled,W is the weight set and P is the port set. Line2~Line4 computes the load on each port. Line5 ~ Line12 decides the coflow scheduling sequence. Firstly, Line6 finds the port which owns the heaviest load. Then Line7 finds the corresponding coflow with the minimal ration of weight and load on that port. Line8~Line10 is adjust process. Line11 gets rid of this coflow from the unschedule sets. After the loop of Line5~Line12, Algorithm 1 will generate the schedule sequence of coflow set.

Within O(n(m+n)) elementary operations, Algorithm 1 will generate the schedule sequence γ, in which Coflow ranks front will be scheduled prior. Although Algorithm 1 has been proved to work well [26] for the offline situation, it has the constraint that assuming coflows arrive at time 0. In practice, coflows arrive dynamically, so that directly using the algorithm is impossible. Some changes should be made to let it work well for the online situation.

B. From offline to online

Algorithm 1 decides coflow's position by the ratio of coflow weight and port load. As today's data centers generally assign jobs with load balancing [16], so that we can make the relaxation of ignoring load difference of each port. When a new coflow comes, we can set the lowest priority to the coflow which has maximum per-port load. Then we get the online approach which is shown as Algorithm 2.

Algorithm 2 is called when a new coflow starts. Different from Algorithm 1, Input of Algorithm 2 is remaining flow size from each port pair. Line2~Line4 computes the load on each port. Instead of considering load diversity on each port, we directly compute the ratio of weight and load at Line5. At last, we sort the ratio of each coflow in non-decreasing order. Comparing with the offline algorithm which has the

Algorithm 2 Online approach to minimize average coflow weight completion time

Input: Coflow set $\mathcal{C}$; active flow *remaining* size $r_{i,j}^{(k)}$ from port i to port j, where $1 \leqslant i \leqslant m, 1 \leqslant j \leqslant m$

Output: γ

1: $W\{1, 2, ...n\} \leftarrow \{w_1, w_2, w_3...w_n\}$
2: $L_i^{(k)} = \sum_{j=1}^{m} r_{i,j}^{(k)}$ for all k $\in \mathcal{C}$ and i $\leq$ m
3: $L_{j+m}^{(k)} = \sum_{i=1}^{m} r_{i,j}^{(k)}$ for all k $\in \mathcal{C}$ and j $\leq$ m
4: $l^{(k)}$= $\max_{1 \leq i \leq 2m} L_i^{(k)}$ for all k $\in \mathcal{C}$
5: $\alpha^{(k)}$=$W[k]/l^{(k)}$ for all k $\in \mathcal{C}$
6: sort$[\alpha^{(1)}, \alpha^{(2)}, \alpha^{(3)}...\alpha^{(n)}]$ in non-decreasing order and set the result to γ

O(n(m+n)) for-do loop, Algorithm 2 only has sort operation at last. If we use insertion sorting, main elementary operations is only O(m+nlogn) and this much faster and easier than Algorithm 1.

C. Distance between the online and offline algorithm

Comparing with the offline 2-approximate algorithm, algorithm 2 ignores load diversity and this may lead to performance loss. In this section we study the performance gap between the online and the 2-approximate offline algorithm. Firstly, we consider the schedule of 500 coflows served by a small-scale cluster consisting of 60 hosts. These hosts are connected with a non-blocking network fabric, where each port (both ingresses and egresses) has the capacity of 1 Gbps. Coflow traces are synthesized with the same real-world parameters detailed in Section VI. Weight of each coflow ranges within 1 to 5. Fig. 1 shows the result.

From Fig. 1,we can see some details of performance gap between the two methods. In total, the online algorithm performs close to the 2-approximate algorithms and it only prolongs the transfer of large coflows. As coflows are generated randomly, we repeat the numerical simulation 200 times. Table I shows the proportions of $\frac{avgcwct\ of\ online}{avgcwct\ of\ 2-appr} - 1$, where $avgcwct$ means average coflow weight completion time. We can see that more than half of the performance loss is less than 0.025. More than 91% cases have the less than 0.1 performance gap and no cases exceed 0.15.

TABLE I: Performance loss result

$\leq 0\%$	≤ 0.025	≤ 0.05	≤ 0.1	≤ 0.15
0	64%	72%	91%	100%

TABLE II: Comparison between the two algorithms

#Scheme	Sched-Mode	Procedure	Performance
2-appr	offline	Complex	High
Yosemite	online	simple	High

We conclude comparing with the offline algorithm, online algorithm has little performance. Indeed, it is much more simple and can maintain relative high performance just as

Table. II shown, so in reality, using the online algorithm to schedule coflow is a good choice.

V. YOSEMITE SYSTEM

In this section, we introduce the design of Yosemite which is a system aims to minimize average coflow weight completion time. Yosemite includes about 4000 lines of java as well as scala code and it follows the actor model like Alluxio [2], hadoop [3],etc. Yosemite uses Akka [1] for message transferring and kryo [4] for object serialization. Code of Yosemite can be downloaded at [7]. In this section, we first introduce actors of Yosemite and the communication between them. Then we introduce the usage of Yosemite.

A. Actors and communication

Algorithm 3 Procedure of bandwidth allocate

Input: Sorted coflow set γ, Remaining capacity for ports set $Rem(.)$
Output: bandwidth of each coflow, Remaing capacity for ports set $Rem(.)$

1: **for** k $\in \gamma$ **do**
2:     Compute Load $g^{(k)}$ according to (5)
3:     **for** $f_{i,j} \in k$ **do**
4:         $b_{i,j} = f_{i,j}/g^{(k)}$
5:         $Rem(P_i^{(in)}) -= b_{i,j}$
6:         $Rem(P_j^{(out)}) -= b_{i,j}$
7:     **end for**
8: **end for**

Fig. 2 shows the architecture of Yosemite. There are two type of nodes: master and worker. Each worker node includes two main components: client and slave. Client contains API daemon and Rate limiter. API daemon is used to interact with applications and Rate Limiter is responsible for throttling flow rate according to the computation result sent from master. Slave has two long running server: data server and comm server. Comm server communicates with master and data server is used to send data. Master node is the brain of the
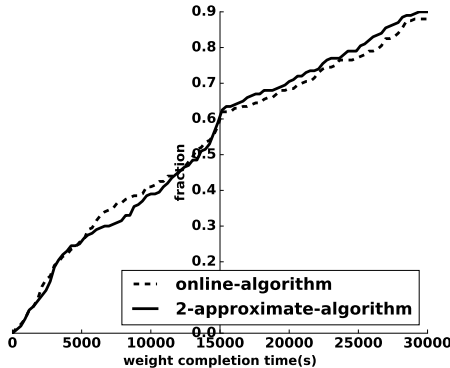

Algorithm 4 Procedure of the master

Input: Coflow F
Output: bandwidth of each flow

1: $\mathcal{C} = \mathcal{C} \cup F$
2: Sort $\mathcal{C}$ according to Algorithm 2
3: Allocate bandwidth to $\mathcal{C}$ according to Algorithm 3
4: Distribute unused bandwidth to $\mathcal{C}$ for all ports
5: Send $b_{i,j}$ to corresponding Slave

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system. It collects coflow information from worker and sends bandwidth information to worker. It also has two components: slave and scheduler. The function of slave is same as that as worker node. Yosemite Scheduler performs coflow sorting and bandwidth computation. Algorithm 4 shows the operation detail of scheduler.

Algorithm 4 is called when a new coflow arrives. Line1~Line2 tries to sort coflow. It calls the online coflow scheduling Algorithm 2. Line3 tries to allocate bandwidth to coflow on the basis of sequence that is computed at Line2. Algorithm 3 has two key steps. Firstly, it computes the bottleneck time of each coflow. The computation method of it is:

$$g^{(k)} = \max(\max_i \frac{\sum_{j=1}^m f_{i,j}^{(k)}}{Rem(P_i^{(in)})}, \max_j \frac{\sum_{i=1}^m f_{i,j}^{(k)}}{Rem(P_j^{(out)})}) \quad (5)$$

Where Rem(.) denotes the remaining bandwidth of an ingress or egress port estimated by the scheduler. (5) gets the slowest time of each coflow according to the bottleneck link. After this, on the base of bottleneck time, it computes $b_{i,j}$ for each flow that transfers from port i to port j Then master updates port available bandwidth as Line5~Line6 shown. After the process of Algorithm.3, scheduler calculates out bandwidth for each flow. At last, scheduler sends the result to each worker, then worker sends flows according to the computation result.

In particular, communication between components is important for a correct distributed, concurrent, fault-tolerant and scalable application. As messages transferring between components needs timely responds, keeping responsive in the face of failure, staying responsive under varying workload.

Fig. 1: performance comparison between 2-approximate algorithm and online algorithm
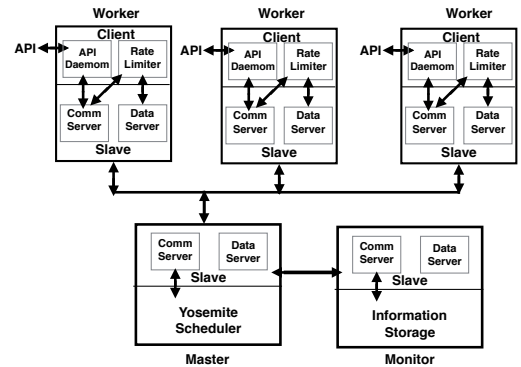

Fig. 2: Yosemite architecture. Computation frameworks interact with Yosemite through a client library

In Yosemite, Comm Server is responsible for this. Comm Server extends Akka [1]. Using the library provided by Akka, Comm Server can provide stable communication for Yosemite components.

B. Work-conserving allocation

Line4 of Algorithm 4 aims to provide work conserving allocation for resources. Just using the computation result of Algorithm 3, extra network resources may be wasted. To prevent this happening, we allocate the remaining bandwidth fair to the corresponding flows that transfer from the port. With work-conserving allocation, resources can be used more efficiency, so that less resources will be wasted.

C. Fault-tolerance

Master is the "brain" of Yosemite. It collects information from slave and computes the bandwidth of each flow. However, for some extreme cases, master may be crushed. If this happened, the system can not work any more. Although Akka provides fault-tolerant strategy which will restart scheduler when it crush down, scheduling information will be lost. To prevent this happen, we start a monitor which stores the real-time state of master. When master collapses, the monitor tries to restart the master and lets it resume the state just the same as no-crushing down. Also, work node may also crash. If this happens, master will try to restart the worker node daemon to let it work normally.

D. API

Yosemite provides API like DOT [32] and Varys [15] to abstract the underlying scheduling and communication mechanisms. User jobs do not require any modifications, but should create Yosemite client to interact with the master. The client of Yosemite provides 4 key API just as Table. III shown.

TABLE III: Yosemite API

Name	parameters	Return	Description
RegisterCoflow	coflowdesc,weight	coflowId	Regisger a coflow
Send	coflowId,size,dst	bool	Send size data to dst
Receive	coflowId	bool	Receive a flow
ReleaseCoflow	coflowId,	bool	Release coflow

Register takes coflow description and weight of the coflow as parameters. After sending the register information to master, coflow id will be returned to worker node. Send tasks coflowId and IP address of destination node as parameters. This method sends a flow that belongs to coflowId. Receive tasks coflowId as the parameter. This method is used to receive data belongs to the corresponding coflow. ReleaseCoflow takes coflowId as the parameter and it is used to release the coflow when finishing transferring.

VI. EVALUATION

We evaluate Yosemite at our openstack [5] platform. Our private cloud can start at most 80 virtual machines (2 Cores, 4GB Mem) simultaneously. To evaluate a slightly larger scale experiments, some VMs will start at most 3 dockers. For larger scale experiments, we use trace-driven simulation. Main results of our evaluation are as follows:

- Running file distribute application at our private cloud platform, we find Yosemite improves $\sim 30\%$ over Varys on minimizing average coflow weight completion time.
- Using facebook trace [15] with randomly generating weight, Yosemite improves about 30%, 40%, 50% over Varys [15], Aalo [13] and Barrat [18] on reducing average coflow weight completion time respectively. However, comparing with Varys, it only has 5% performance on reducing average coflow completion time.
- Under different settings, including length, width, weight and concurrent number, we find Yosemite works better under larger coflow length variance, width variance, weight variance and concurrency.
- Comparing with the LP-based algorithm [29] , Yosemite has only about less than 10% performance loss.

A. methlogy

Experiment settings . In some of our experiment we use the traffic of Facebook that was collected on a 3000-machine cluster with 150 racks [15]. As the original trace does not contain information of weight setting, we randomly generate weight within 1 to 10. The original cluster had a 10 : 1 core-to-rack oversubscription ratio with a total bisection bandwidth of 300 Gbps. Due to hardware limits, in our testbed experiment, we limit the bandwidth of ingress and egress port capacity to 1Gbps but maintain the characters of the original traffic. In our experiment, coflows are categorized to be four types in terms of their length (the size of the largest flow in bytes for a coflow) and width (the number of parallel flows in a coflow): Narrow&Short, Narrow&Long, Wide&Short, and Wide&Long, where a coflow is considered to be short if its length is less than 100 MB, and narrow if it involves at most 20 flows.

Metrics. In our experiment, metric for comparison is the improvement in average coflow weight completion time of coflows and jobs (when its last task finished) in the workload. The definition of improvement A over B is
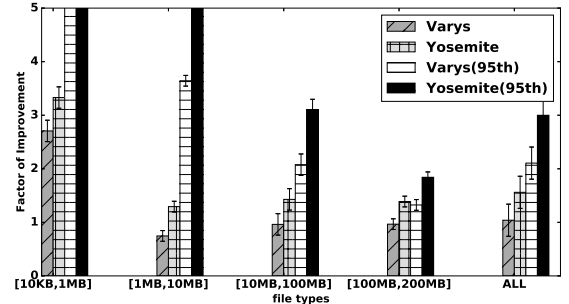

Fig. 3: [cloud] File distribute application performance comparison

$$Factor\ of\ improvement = \frac{avg\ cwct\ of\ B}{avg\ cwct\ of\ A} \qquad (6)$$

Where, avg cwct means average coflow weight completion time. In our experiment, default baseline is TCP fair-sharing.

Open source. To make our experiment repeatable, we publish main code of Yosemite as well as Yosemite-Sim. Dockerfile which used to generate Yosemite docker image is also included at the source code and all the sources can be downloaded at [7]. For larger scale of experiment in this paper, we use trace-driven simulation. Main codes of the simulation including trace generator code can be downloaded at [8].

B. Cloud platform evaluation

We deploy Yosemite at our private openstack platform which can start at most 80 virtual machines (2 Cores, 4GB Mem) simultaneously. Operation system of virtual machine is Ubuntu16.04. With the help of Traffic Control module [6], we constrain the maximum bandwidth of each VM's NIC to 1GB/s.

Firstly, we run file distribute application to test the performance of Yosemite. Each virtual node constantly construct files whose size ranging from 1KB to 200MB. Weight of each job is randomly generated ranging from 1 to 10. Destination is randomly chosen from K($K \leq 80$) nodes. Job can be regarded as finished until all the K nodes receive the file. TCP-fair is chosen as the baseline, Fig. 3 shows performance comparison between Yosemite and Varys. We repeat the process 10 times and the error bar indicates the max, min and average factor of improvement. To decrease the influence of extreme values, we remove the top and last 2.5% of each methods and recompute the factor of improvement, then we get the 95th factor of improvement. From Fig. 3, we can see improve factor of Yosemite is 3.1 , while that of Varys is 2.1 in total. Yosemite improves more than 30% than Varys. Specially, Yosemite improves more for small files than large files.

Work conserving aims to allocate the spare network resources to flows, as a result, network resources will be used more efficiently. Efficient network utilization will accelerate the transfer process. In Yosemite, scheduler allocate the spare bandwidth to flows equally to guarantee resources utilization. Fig. 4 shows the improvement of this step. We can see that
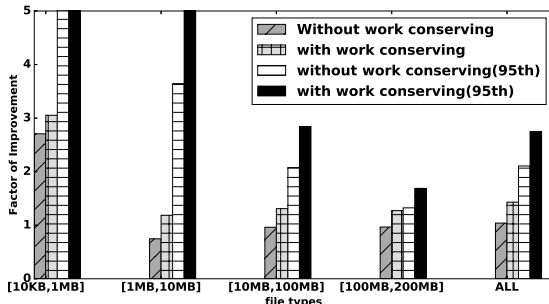

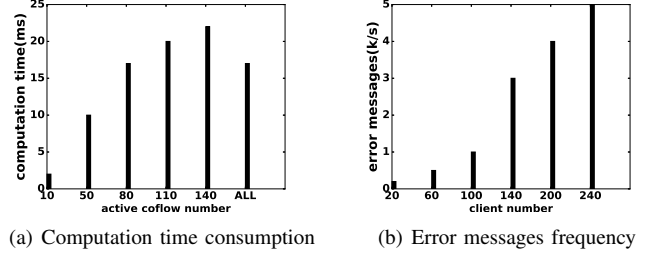(a) Computation time consumption   (b) Error messages frequency

Fig. 5: [cloud] Overheads of Yosemite

with work conserving, factor of improvement of Yosemite is 2.1 in total, while that drops to 1.8 without work conserving.

Computation rate is an important property for the master scheduler. scheduler should be fast enough to compute out the scheduler order of coflows. Fig. 5(a) shows the computation rate of Yosemite scheduler. We can see for peak load, when active coflows is 140, computation time of the scheduler is ~23ms and average computation time is less than 17ms. Messages transferring between comm server is the main overheads of Yosemite system. Error messages occurs when component crashes and server resources are insufficient. As 80 VMs in our platform will reach full load, we start $1 \sim 3$ docker at each VM to get a slightly larger scale experiment. Fig. 5(b) shows the error messages frequency. We can see that when the concurrent worker number is over 200, peak error messages is over 4k/s.

Write down the trace of distribute file application and let the simulator run the trace under the same parameter. Fig. 6 shows the performance gap between Yosemite and trace-driven simulator. We can see performance gap between cloud platform and Yosemite is narrow($< 15\%$). In the following section, we use our trace-driven simulator to do some larger experiments.

C. Trace-driven simulation

We use the trace from Facebook Hadoop/Hive trace to test the performance of Yosemite. Weight in our experiment are uniform distribution generated between 1 and 10. We repeat
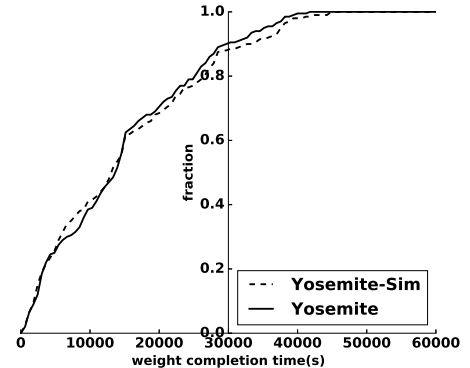

Fig. 4: [cloud] with and without work conserving comparison

Fig. 6: [cloud] performance comparison between Yosemite and Yosemite-sim under the same setting

the experiment 100 times and Fig .7 shows the result of the weight coflow completion time of Yosemite, Barrat, Varys, Aalo, perflow fairness. Perflow fairness is selected as the baseline.

Fig. 7(a) implies that Yosemite greatly reduces the average and 95th percentile weight coflow completion time across all coflow types. The improvement factors of Yosemite on average weight coflow completion time are 3.5 (Narrow&Short),1.6 (Narrow&Long), 1.7 (Wide&Short), 1.4 (Wide&Long), and 1.5 (ALL), while that of Varys are 2.4 (Narrow&Short),0.9 (Narrow&Long), 1.2 (Wide&Short), 1.3 (Wide&Long), and 1.2 (ALL). We generate weight 100 times and repeat the experiment, the error bar indicates the maximum and minimum improvement. To eliminate the influence of extreme value, we get the 95th of the improvement which gets rid of the top and last 2.5% value. For the 95th situation, we can find that Yosemite has the improvement factors on average weight coflow completion time of 30 (Narrow&Short),20 (Narrow&Long), 2.5 (Wide&Short), 1.5 (Wide&Long), and 2.5 (ALL), however Varys has 22 (Narrow&Short),14 (Narrow&Long), 2.1 (Wide&Short), 1.2 (Wide&Long), and 2.1 (ALL) and other method such as Aalo and Barrat performs even worse than Varys. Fig. 7(a) also indicates that FIFO_LM based solution such as Barrat only accelerates the transmission of long task (including Narrow&Long and Wide&Long), however, for the short ones, it has poor performance. This is because that Barrat uses FIFO_LM based solution can lead to head-of-line blocking problem especially for the heterogenous coflows which has various flow length, width and arrival time.

Fig. 7(b) is the CDF of weight completion time of different schemas. We can see comparing with perflow-fairness schema, through Yosemite and other schemas can reduce weight completion time on average, they prolong the tail value. That is to say, for applications which involves lot long flows, weight completion time may have long duration using Yosemite. This is trivial for private cloud.

Comparing with Varys, Aalo and other schemas, Yosemite can reduce weight completion significantly. One may be interested in the coflow completion time under different schema. Fig. 8 shows the detail of the coflow completion time of Yosemite, Barrat, Varys, Aalo, perflow fairness of the same settings, perflow fairness is selected as the baseline. Fig. 5(a) shows that the improvement factors of Yosemite on average coflow completion time are 2 (Narrow&Short),1.1 (Narrow&Long), 0.8 (Wide&Short), 0.9 (Wide&Long), and 1.3 (ALL) on average while Varys performs about $\sim 5\%$ better than Yosemite. Fig. 8(a) also shows the maximum value and minimum value of Yosemite under different weight settings. For Barrat, Aalo and Varys, their coflow completion time are same no matter what weight are set. Fig. 8(b) shows the result of distribution of coflow completion time. The result is similar to Fig. 7(b).

D. Performance under different settings

In this section, we will test the performance of Yosemite under different settings. From the detail of the online algorithm, we can see that the performance of it is affected by coflow length, coflow width, weight settings and its concurrency. In this part, we will explore its performance from the four aspects.

TABLE IV: Default parameters in each group of experiment

Number	Length	Width	Weight	Arriva	Capacity
512	[100KB,10GB]	60	[1,10]	[0s,1000s]	1GB

As we want to explore the influence of each parameter, so in each group of experiment, we should fix the value of other parameters and only change the factor we want to study. Table .IV shows the default settings of each experiment. In each group of experiment, we start 512 coflows. Length of each coflow are generated between 100KB to 10GB. Width of each coflows are 60. Weight of each coflows are within 1 to 10. Arrival time of each coflow is between 0 and 1000s. Ingress and egress port capacity in our experiment are 1GB. For each group of experiment, we generate parameters 100 times and we draw maximum value, minimum value, average value in the picture.

1) Impact of coflow length: In this group of experiment, we test the influence of coflow length. Coflow width, weight, arrival time are set as Table.IV. In each group of experiment, the value of coflow width,weight and arrival time are same, we only change length of coflow. Coflow length in our experiment are set within [100KB,K]. Varying K from 100MB to 900MB. Fig. 9 (a) shows the result. From Fig. 9 (a) we can see that with the increasing of K, improvement of Yosemite becomes larger. For example, when K is 100MB, improvement of Yosemite is 2 and when K is 900MB, improvement of Yosemite is 3. This means, when K becomes larger, length differentiation between coflows becomes larger, scheduling result is better.

2) Impact of coflow width: Fig. 9(b) shows the influence of coflow width. In this group of experiment, we vary the fraction of thin coflows(width< 30) from 20% to 40%. Coflow length, coflow weight, time arrival of coflow are set as Table. IV shown. From Fig. 9(b) we can see that with the increasing of thin coflows fraction, fraction of improvement of Yosemite becomes smaller. The reason for this is that, when fraction of thin coflows is small, conflict probability between coflows is large, so it is necessary to decide a suitable scheduling sequence of coflows.

3) Impact of coflow weight: Weight indicates the importance of the application in reality. Weight setting has huge influence on the performance of weight coflow completion time. In this section, we study the influence of weight. In this group of experiments, Coflow length, width and arrival time are set according to Table .IV. Coflows' weight are generated between $[8-\sigma, 8+\sigma]$, varying σ from 1 to 5. Fig. 9(c) shows the result. From Fig. 9(c) we can see that when weight variance σ becomes larger, Improvement of Yosemite becomes larger.

4) Impact of coflow concurrency: In real word, coflow can start at any time. Arrival time of coflows can impact the traffic load in data center network. In this part, we explore the impact of coflow concurrency. Changing the number of coflows that start concurrency. Fig. 9(d) shows the result. We can see that with the concurrent number of coflows increasing,
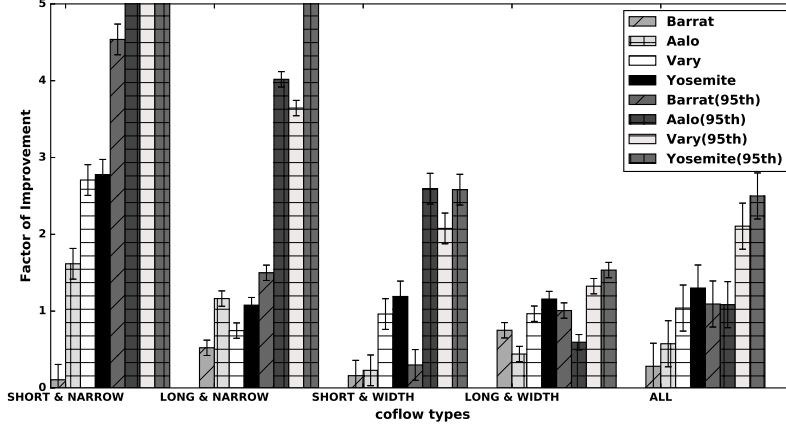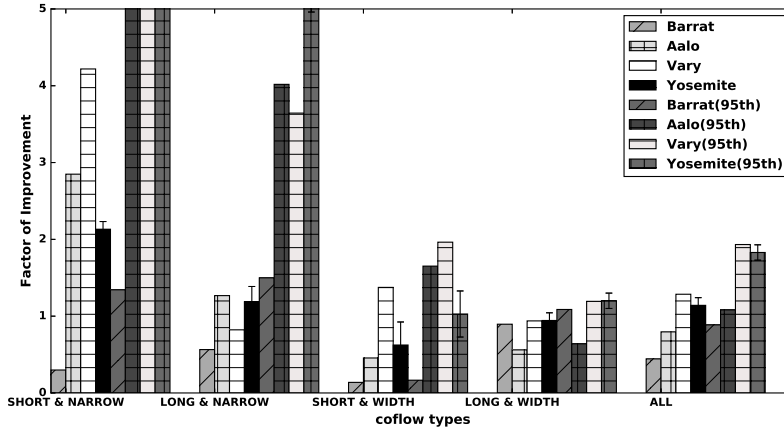
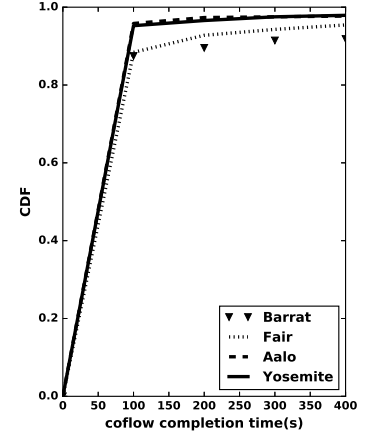(a) Improvement weight coflow completion time comparison
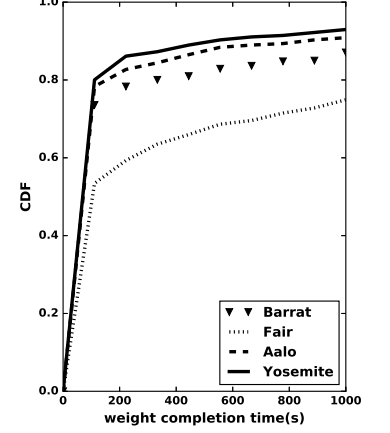
(b) Weight coflow completion time comparison(s)

Fig. 7: Detail of the weight coflow completion time of Yosemite, Barrat, Varys, Aalo, perflow fairness with real data center traffic trace, perflow fairness is selected as the baseline.
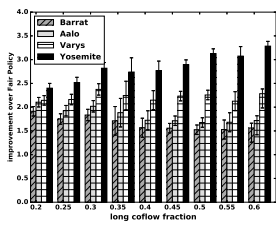

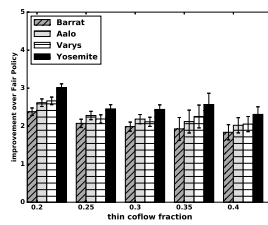(a) Improvement of coflow completion time
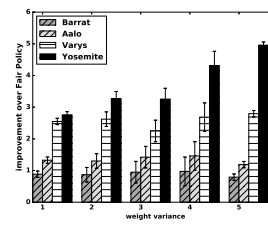
(b) coflow completion time comparison(s)

Fig. 8: Detail of the coflow completion time of Yosemite, Barrat, Varys, Aalo, perflow fairness with real data center traffic trace, perflow fairness is selected as the baseline.
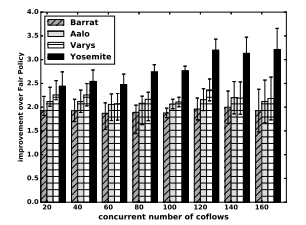

(a) Impact of coflow length   (b) Impact of coflow width   (c) Impact of coflow weight   (d) Impact of coflow concurrency

Fig. 9: Yosemite performance comparison with Baraat and Varys, Aalo under different settings, perflow fairness is selected as the baseline.

improvement of Yosemite becomes larger. This is because, the heavier the network load is, the larger optimization space there is for preemptive scheduling schemes

E. Distance to Optimiztion

It is hard to find the optimal schedule is infeasible, we tried to find an LP-based solution [29]. Using the facebook trace, weight are generated between 1 to 5. Repeated the

experiment 20 times. We get the experiment result just as Fig. 10 shown. We can see that on total Yosemite has less than 10% performance loss. For Narrow&Short coflow set, Yosemite has about 15% performance loss, for Narrow&Long,Yosemite even performs better, and for the other coflow set, Yosemite has about 5% performance loss.

VII. CONCLUSION

In this paper, we use weight to quantify the importance of applications. Coflows belonging to more important applications will have larger weight. We design and implement Yosemite-a coflow scheduling system that aims to minimize average coflow completion time. We test the performance of it by trace-driven simulation and test-bed evaluation. Experiments show Yosemite can reduce average coflow weight completion time significantly.

Although Yosemite works well on minimizing average coflow weight completion time, It is Clairvoyant method and this constraints its usage. Indeed in data center network, applications such as file backup, file distributes can know these information. For some computation applications, it is hard to get. As a result, in the future, we will make advance of Yosemite to let it work in Non-Clairvoyant way.

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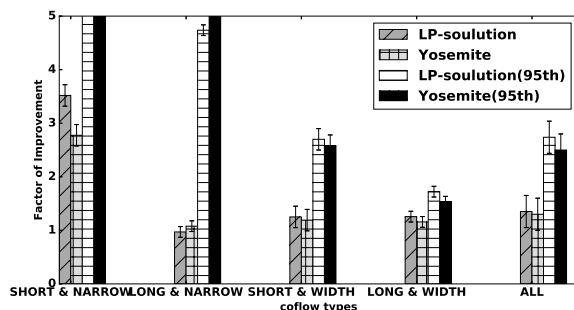
Fig. 10: performance comparison between the LP-based solution and Yosemite