Metaflow: A DAG-Based Network Abstraction for Distributed Applications

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1 Introduction

The purpose of network optimization is to boost the distributed application performance. In the past decade, increasingly network scheduling techniques have been proposed to achieve this goal which focus on network metrics in different levels. Flow-level metrics, such as flow completion time (FCT) and per-flow fairness, are based on the abstraction of flows yet they cannot capture the semantics of communication in a cluster application. Therefore, flow-level metrics can be at odds with application-level goals. Being aware of this problem, coflow [1] is proposed as a new network abstraction. It is a major leap forward of application-aware network scheduling. Minimizing the average coflow completion time (CCT) usually aligns application-level performance, thereby actually decreasing job completion time (JCT). However, the coflow abstraction is insufficient to reveal the dependencies between computation and communication. As a result, the real application performance can be hurt, especially in the absence of hard barriers.

For example, a scheduling problem is shown in Figure 1. In this case, there are two jobs J1 and J2 and every job has a coflow (C1 and C2). C1 has one flow transferring 3 units of data from machine 2 to machine 1, while C2 has two flows transferring 3 and 1 units of data from machine 1 and machine 2 to machine 3. Additionally, the subsequent computation of J1 and J2 is performed in machine 1 and machine 3 respectively. The dependencies between flows and computation are described with DAGs shown in Figure 1b. To minimize average CCT, the optimal schedule is shown in Figure 1c and the average CCT is just $\frac{3+4}{2} = 3.5$ units of time. Besides, based on DAGs of jobs, the average JCT can be calculated which is $\frac{6+10}{2} = 8$ units of time.

As a comparison, Figure 1d shows a different scheduling. Obviously, it introduces more overlaps between communication and computation. Thus, the average JCT is reduced to $\frac{7+7}{2} = 7$ units while the CCT ($\frac{4+4}{2} = 4$) is higher.

![Figure 1: A motivation example](image)

![Figure 2: A metaflow example](image)

In this paper, we propose a new abstraction namely metaflow that resides in the middle of the two extreme points of flows and coflows. Each metaflow is a collection of flows consumed by the same computation task in the DAG of one job. The job is assumed to be executed in a distributed environment in data level parallelism manner.

Considering an example job in Figure 2a with 4 sending and 2 receiving machines, all flows are classified into one coflow. Meanwhile, following the definition of metaflow, these flows are divided into 4 metaflows, denoted with different colors. Each metaflow is connected to an exclusive computing task, as shown in Figure 2b. Regarding the DAG, a metaflow is the smallest unit to forward the computation progress.
2 Scheduling Algorithms

We propose a metaflow-based scheduling algorithm (MSA) to schedule the metaflows, as detailed in Algorithm 1. It has three main steps: firstly, we calculate the performance gain brought by each metaflow; then, all active metaflows are sorted according to their gains in decreasing order; at last, the available bandwidth is assigned to each metaflow in order.

**Performance gain estimation.** Metaflow’s gain can be classified into two categories, direct and indirect gain, according to whether this metaflow can invoke the computation independently. If it could, the gain of this metaflow is calculated in two steps: first the computation load of these tasks are summed up, and then divided by the remained size of the metaflow. For example, the metaflow 1 and 2 in Figure 2b both can result subsequent computing tasks dependently, that is to say, it has to wait other unfinished metaflows. For this kind of metaflows, the attributes are set to the total metaflow sizes needed to start the computing task. In Figure 2b, metaflow 3 and 4 belong to this kind, and the attributes of them are \((\text{reSize}_{MF1} + \text{reSize}_{MF2})\) and \((\text{reSize}_{MF1} + \text{reSize}_{MF2} + \text{reSize}_{MF3} + \text{reSize}_{MF4})\).

**Sorting.** Metaflows which have direct profits are superior to that which have indirect profits. In their individual group, metaflows with larger direct profit and smaller indirect profit are given higher priorities.

**Bandwidth assignment.** For a selected metaflow, it contains flows go to all reducers of this job. Since the JCT is the maximum finish time of these reducers, all reducers are expected to finish simultaneously. Some existing algorithms have been proposed to this intent, say MADD [2], we can adopt these algorithms directly. After assign bandwidth to a metaflow, the available bandwidth in this time slot is updated and the assignment of next metaflow begins. This assign process ends until all metaflows are considered or no bandwidth resource is left.

**Algorithm 1 Metaflow Scheduling Algorithm (MSA)**

```
1: if (metaflow arrives or finishes) then
2:   if no unfinished metaflows then
3:     break
4:   end if
5: extract all unfinished metaflows
6: for unfinished metaflow, do
7:   calculate the gain of metaflow
8: end for
9: sort metaflows based on profit
10: for metaflow in the sorted list do
11:   assign bandwidth to metaflow (e.g. MADD)
12: end for
13: end if
```

3 Preliminary Results

In this section, we evaluate the performance of MSA for a single job using a flow-level simulator. We take the collected Facebook logs [2] as our workload. The Facebook logs lack the DAG information of jobs, thus we generate the DAGs for each job. Figure 3a illustrates three types of topologies we use, which are partial order, disorder and total order respectively.

For each topology, we randomly select 50 jobs from the workload and compute the average JCT as results. We compare MSA with a coflow-based scheduling algorithm (Varys) [2]. As shown in Figure 3b, MSA outperforms Varys by 1.78× and 1.53× for DAGs in total order and partial order separately. Even in presence of the hard barrier, MSA is equivalent to Varys and achieves the same JCT. In summary, metaflow-based scheduling can effectively improve the distributed application performance.

4 Ongoing Work

As part of our current work, we are trying to deploy metaflow into real clusters. Our end goal is to design a self-driven system which automatically detects and schedules the metaflows to optimize the applications’ performance. As a first step, we plan to devise a learning based mechanism that can distinguish metaflows along with their attributes using collected network statistics. Further, the routing strategies of metaflows will be investigated, which is an indispensable component in real network.

**References**

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