Coflow

Recent Advances and What's Next?

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Big Data

The volume of data businesses want to make sense of is increasing

Increasing variety of sources

• Web, mobile, wearables, vehicles, scientific, ...

Cheaper disks, SSDs, and memory

Stalling processor speeds



Big Datacenters for Massive Parallelism



Data-Parallel Applications

Multi-stage dataflow

Computation interleaved with communication

Computation Stage (e.g., Map, Reduce)

- Distributed across many machines
- Tasks run in parallel

Communication Stage (e.g., Shuffle)

Between successive computation stages



Communication is Crucial

Performance

Facebook jobs spend $\sim 25\%$ of runtime on *average* in intermediate comm.¹

As SSD-based and in-memory systems proliferate, the network is likely to become the primary bottleneck

I. Based on a month-long trace with 320,000 jobs and 150 Million tasks, collected from a 3000-machine Facebook production MapReduce cluster.

Transfers data from a source to a destination

Independent unit of allocation, sharing, load balancing, and/or prioritization

Faster Communication Stages: Networking Approach

"Configuration should be handled at the system level"

Existing Solutions D³ DeTail PDQ PFabric WFQ CSFQ DCTCP GPS RED ECN XCP D²TCP FCP RCP 2005 2010 2015 1980 2000s 1990 **Per-Flow Fairness Flow Completion Time**

Independent flows cannot capture the collective communication behavior common in data-parallel applications

Why Do They Fall Short?







Flow

Why Do They Fall Short?





Why Do They Fall Short?





Solutions focusing on flow completion time cannot further decrease the shuffle completion time

Improve Application-Level Performance¹





Communication abstraction for data-parallel applications to express their performance goals

- I. Minimize completion times,
- 2. Meet deadlines, or
- 3. Perform fair allocation.







Enables coflows in data-intensive clusters



Communication abstraction for data-parallel applications to express their performance goals

- I. Coflow Scheduler
- 2. Global Coordination
- 3. The Coflow API

Faster, application-aware data transfers throughout the network

Consistent calculation and enforcement of scheduler decisions

Decouples network optimizations from applications, relieving developers and end users

- I. The size of each flow,
- 2. The total number of flows, and
- 3. The endpoints of individual flows.

I. Efficient Coflow Scheduling with Varys, SIGCOMM'2014



1. Finishing Flows Quickly with Preemptive Scheduling, SIGCOMM'2012. 2. pFabric: Minimal Near-Optimal Datacenter Transport, SIGCOMM'2013.

Inter-Coflow Scheduling is NP-Hard

	Coflow I	Coflow 2	
Link 2		6 Units	
Link I	3 Units	2 Units	
	``/	 `/	

Concurrent Open Shop Scheduling¹

- Examples include job scheduling and caching blocks
- Solutions use a **ordering** heuristic

1. Finishing Flows Quickly with Preemptive Scheduling, SIGCOMM'2012. 2. pFabric: Minimal Near-Optimal Datacenter Transport, SIGCOMM'2013.

Inter-Coflow Scheduling is NP-Hard



Concurrent Open Shop Scheduling with Coupled Resources

- Examples include job scheduling and caching blocks
- Solutions use a **ordering** heuristic
- Consider matching constraints





Employs a two-step algorithm to minimize coflow completion times

- I. Ordering heuristic
- 2. Allocation algorithm

Keep an ordered list of coflows to be scheduled, preempting if needed Allocates minimum required resources to each coflow to finish in minimum time

Ordering Heuristic



	$C_1 \text{ ends}$ $C_2 \text{ ends}$ $C_3 \text{ ends}$
L	0,
L	02
L	03
L.	
1	
1	Shortest-First
÷ .	(Total CCT = 35)
١	
L	

Ordering Heuristic



Width



C₁ ends

01



Ordering Heuristic





	C ₃ ends	C2 ends	C ₁ ends
+			
0,			
			-
02			
0.1			_
V3			
L			>
	6	16	19
	Ilme	=.	» ≮>
Nar	rowes	st-Firs	t (41)

Ordering Heuristic







Smallest-Bottleneck (31)

Allocation Algorithm

A coflow cannot finish before its very last flow





Enables coflows in data-intensive clusters

- I. Coflow Scheduler
- 2. Global Coordination
- 3. The Coflow API

Faster, application-aware data transfers throughout the network Consistent calculation and enforcement of scheduler decisions Decouples network optimizations from

applications, relieving developers and end users

The Need for Coordination





The Need for Coordination



Uncoordinated local decisions interleave coflows, hurting performance

Varys Architecture

Centralized master-slave architecture

• Applications use a client library to communicate with the master

Actual *timing* and *rates are* determined by the coflow scheduler





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Faster, application-aware data transfers throughout the network

Consistent calculation and enforcement of scheduler decisions

Decouples network optimizations from applications, relieving developers and end users

I. Download from http://varys.net



Evaluation

A 3000-machine trace-driven simulation matched against a 100-machine EC2 deployment

- I. Does it improve performance?
- 2. Can it beat non-preemptive solutions?
- 3. Do we really need coordination?



Better than Per-Flow Fairness			
Comm. Heavy Comm. Improv. Job Improv.			
EC2	3.16X	2.50X	
Sim.	4.86X	3.39X	

Better than Per-Flow Fairness

	Comm. Improv.	Job Improv.
EC2	1.85X	1.25X
Sim.	3.21X	1.11X

Preemption is Necessary [Sim.]





Preemption is Necessary [Sim.]



I. Managing Data Transfers in Computer Clusters with Orchestra, SIGCOMM'2011

I. Managing Data Transfers in Computer Clusters with Orchestra, SIGCOMM'2011

Lack of Coordination Hurts [Sim.]



I. Managing Data Transfers in Computer Clusters with Orchestra, SIGCOMM'2011 2. Finishing Flows Quickly with Preemptive Scheduling, SIGCOMM'2012 3. pFabric: Minimal Near-Optimal Datacenter Transport, SIGCOMM'2013 4. Decentralized Task-Aware Scheduling for Data Center Networks, SIGCOMM'2014 Smallest-flow-first (per-flow priorities) • Minimizes flow completion time

FIFO-LM⁴ performs decentralized coflow scheduling

· Suffers due to local decisions • Works well for small, similar coflows

Coflow

Communication abstraction for data-parallel applications to express their performance goals

I. The size of each flow.

- 2. The total number of flows, and
- 3. The endpoints of individual flows. Task failures and restarts
- Pipelining between stages
- ← Speculative executions

How to Perform Coflow Scheduling Without Complete Knowledge?



Efficiently schedules coflows without complete and future information

- I. Current size is a good predictor of actual size
- 2. Set priority that decreases by how much a coflow has sent
- 3. Discretize priority levels to blend in FIFO within each level

1. Efficient Coflow Scheduling Without Prior Knowledge, SIGCOMM'2015

How to Perform Coflow Scheduling *Without* Changing the Applications?



Efficiently schedules coflows **without** changing applications^{*}

- I. Learn coflows online from traffic patterns
- 2. Error-tolerant scheduling to survive learning errors
- 3. Limited to jobs with single coflows

I. CODA: Toward Automatically Identifying and Scheduling Coflows in the Dark, SIGCOMM'2016

What About Fair Coflow Scheduling?

HUG

Fairly schedules coflows instead of trying to minimize CCT

- I. Multi-resource fairness with high utilization
- 2. Fairness-utilization tradeoff results in prisoner's dilemma

I. HUG: Multi-Resource Fairness for Correlated and Elastic Demands, NSDI'2016



Better capture application-level performance goals using coflows

Coflows improve application-level performance and usability

• Extends networking and scheduling literature

Coordination – even if not free – is worth paying for in many cases

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Improve Flow Completion Times



Distributions of Coflow Characteristics







Traffic Sources

- I. Ingest and replicate new data
- 2. Read input from remote machines, when needed
- 3. Transfer intermediate data
- 4. Write and replicate output





Distribution of Shuffle Durations

Performance

Facebook jobs spend $\sim 25\%$ of runtime on average in intermediate comm.



Month-long trace from a 3000machine MapReduce production cluster at Facebook

320,000 jobs 150 Million tasks

Theoretical Results

Structure of optimal schedules

• Permutation schedules might not always lead to the optimal solution

Approximation ratio of COSS-CR

• Polynomial-time algorithm with constant approximation ratio $(-\frac{64}{2})^{\dagger}$

The need for coordination

• Fully decentralized schedulers can perform arbitrarily worse than the optimal

1. Due to Zhen Qiu, Cliff Stein, and Yuan Zhong from the Department of Industrial Engineering and Operations Research, Columbia University, 2014



Employs a two-step algorithm to support coflow deadlines

- I. Admission control
- 2. Allocation algorithm

Do not admit any coflows that cannot be completed within deadline without violating existing deadlines Allocate minimum required resources to each coflow to finish them at their deadlines

More Predictable



Experimental Methodology

Varys deployment in EC2

- 100 m2.4xlarge machines
- Each machine has 8 CPU cores, 68.4 GB memory, and 1 Gbps NIC
- ~900 Mbps/machine during all-to-all communication

Trace-driven simulation

- Detailed replay of a day-long Facebook trace (circa October 2010)
- 3000-machine, 150-rack cluster with 10:1 oversubscription