Orchestra

Managing Data Transfers in Computer Clusters

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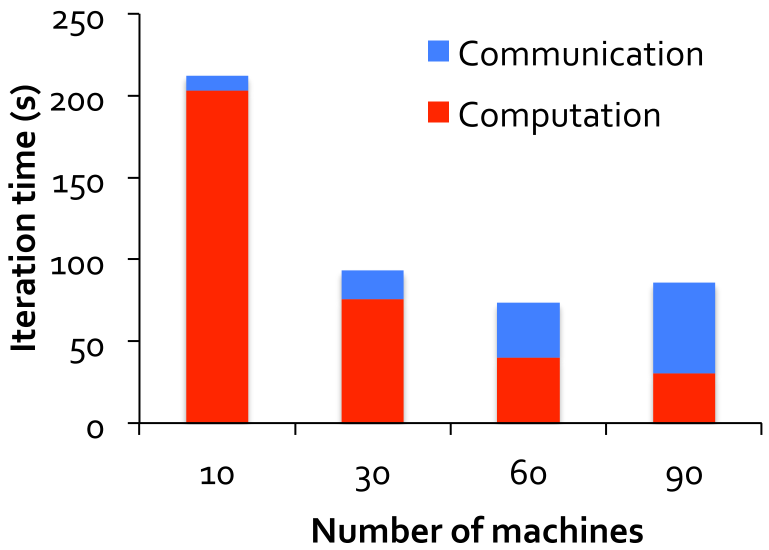
Moving Data is Expensive

Typical MapReduce jobs in Facebook spend 33% of job running time in large data transfers

Application for training a spam classifier on Twitter data spends 40% time in communication

Limits Scalability

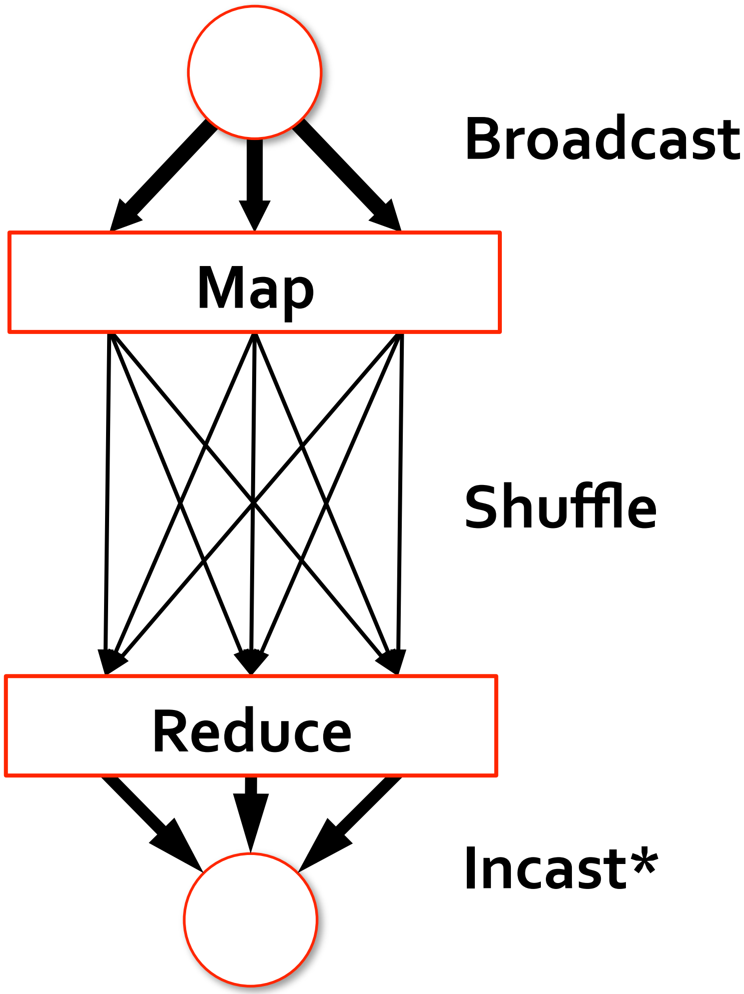
Scalability of Netflix-like recommendation system is bottlenecked by communication



Did not scale beyond 60 nodes

» **Comm. time increased faster than comp. time decreased**

Transfer Patterns



Transfer: set of all flows transporting data between two stages of a job

» Acts as a *barrier*

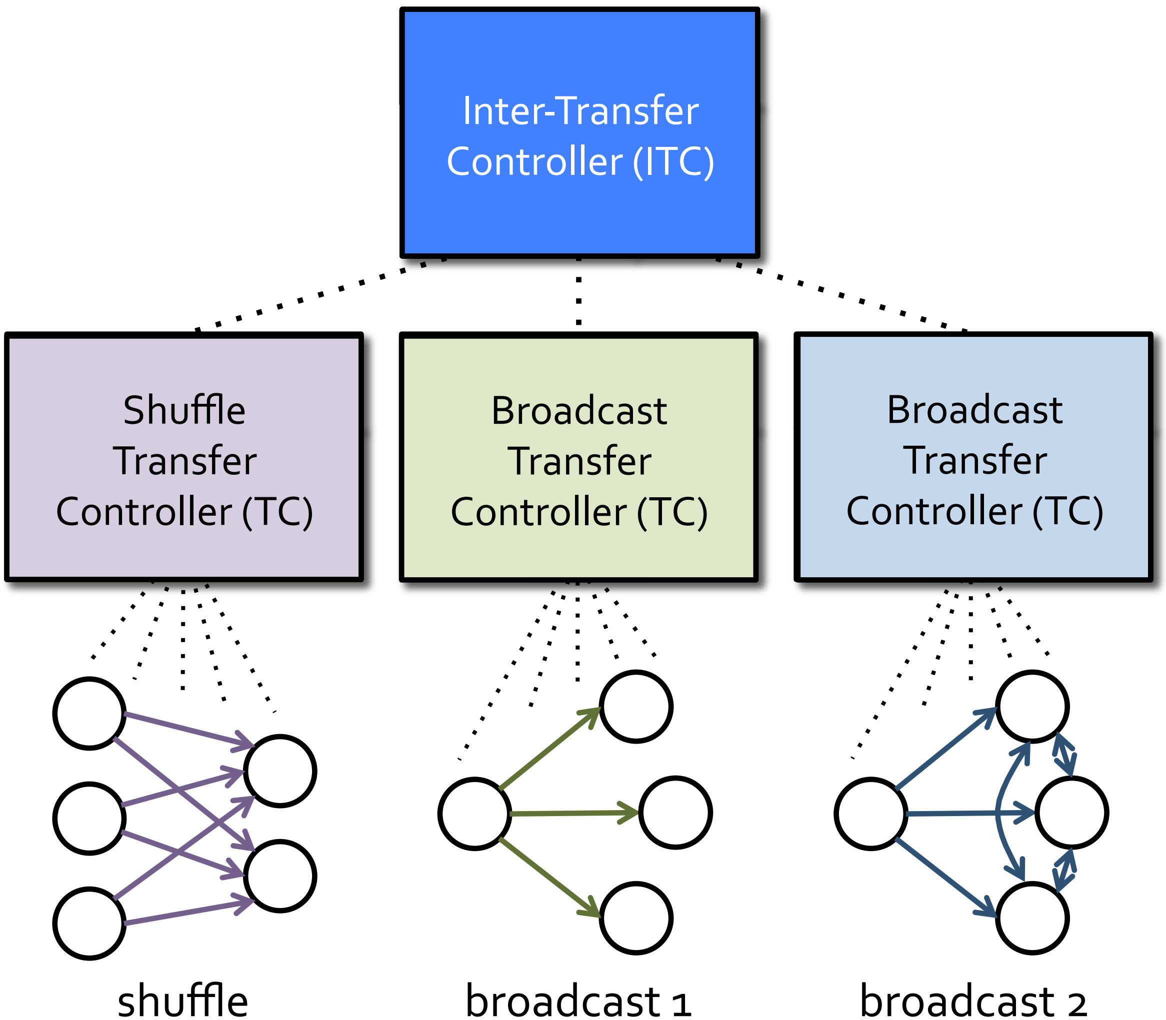
Completion time: Time for the last receiver to finish

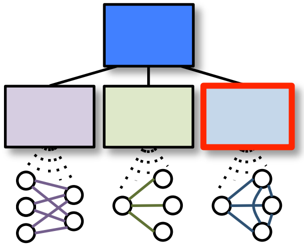
Contributions

1. Optimize at the level of transfers instead of individual flows

2. Inter-transfer coordination

Orchestra


Inter-Transfer
Controller (ITC)
Shuffle
Transfer
Controller (TC)
Broadcast
Transfer
Controller (TC)
Broadcast
Transfer
Controller (TC)
shuffle
broadcast 1
broadcast 2



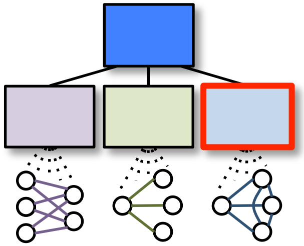
Cornet: Cooperative broadcast

Broadcast same data to every receiver

» Fast, scalable, adaptive to bandwidth, and resilient

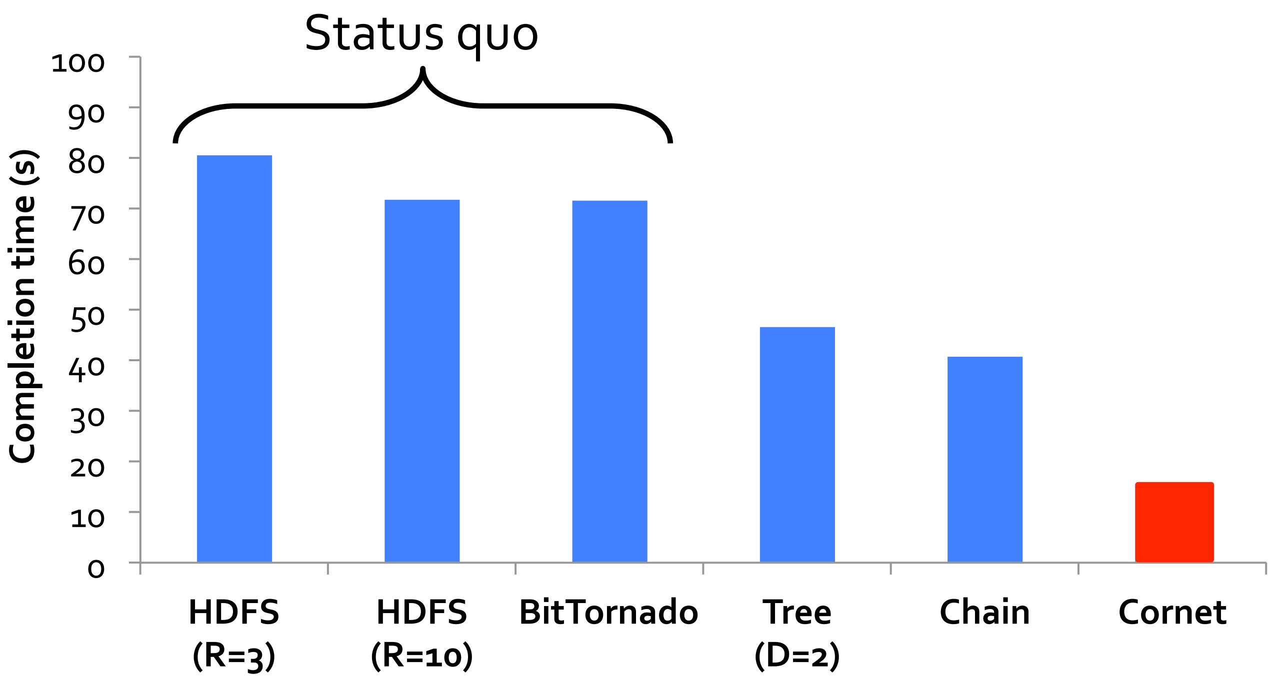
Peer-to-peer mechanism optimized for cooperative environments

Observations	Cornet Design Decisions
1. High-bandwidth, low-latency network	✓ Large block size (4-16MB)
2. No selfish or malicious peers	✓ No need for incentives (e.g., TFT) ✓ No (un)choking ✓ Everyone stays till the end
3. Topology matters	✓ Topology-aware broadcast



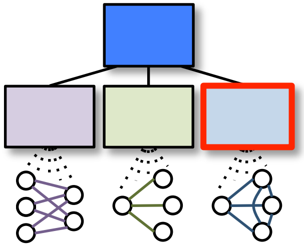
Cornet performance

1GB data to 100 receivers on EC2



4.5x to 5x improvement

Topology-aware Cornet



Many data center networks employ tree topologies

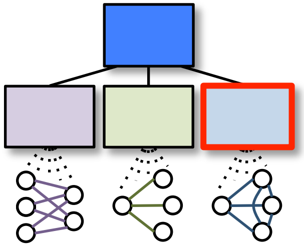
Each rack should receive exactly one copy of broadcast

» Minimize cross-rack communication

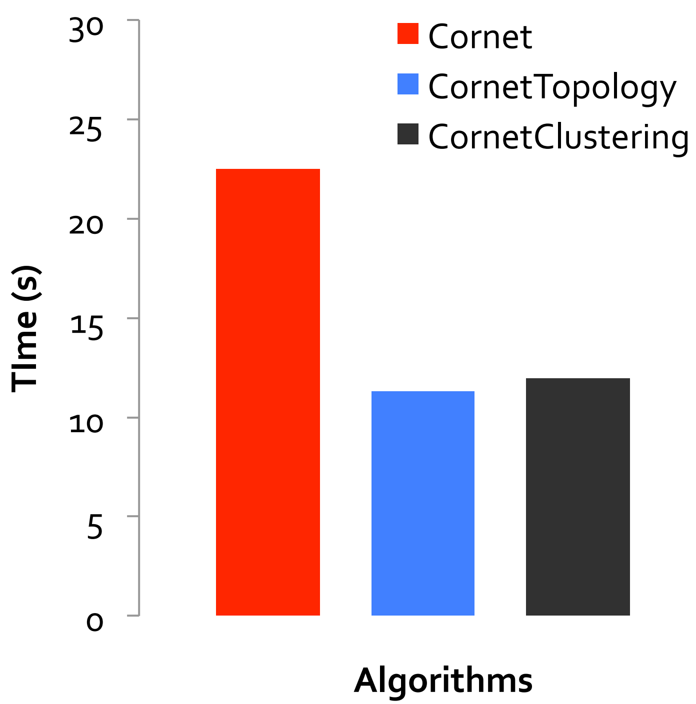
Topology information reduces cross-rack data transfer

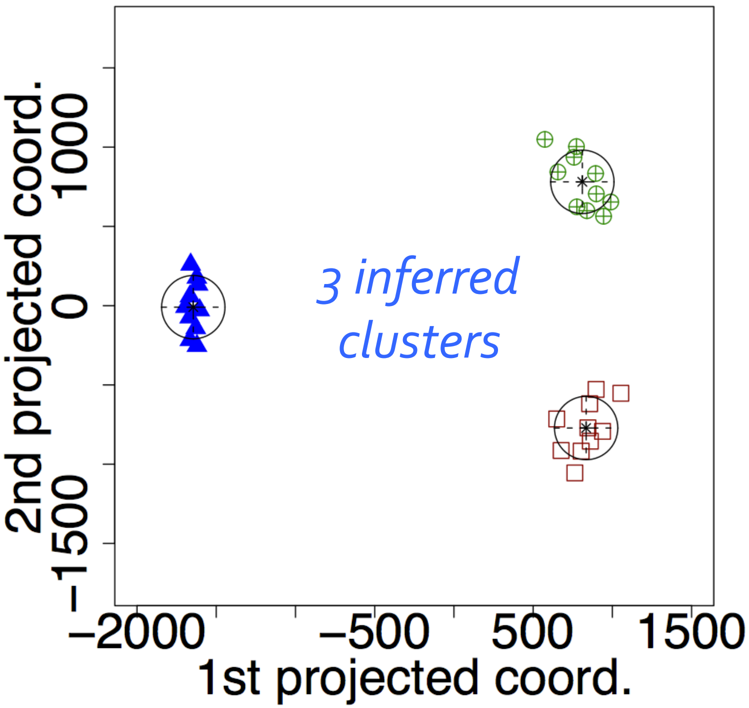
» Mixture of spherical Gaussians to infer network topology

Topology-aware Cornet



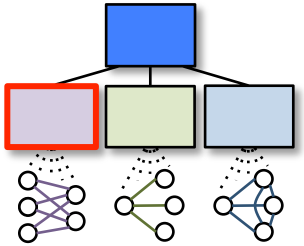
200MB data to 30 receivers on DETER

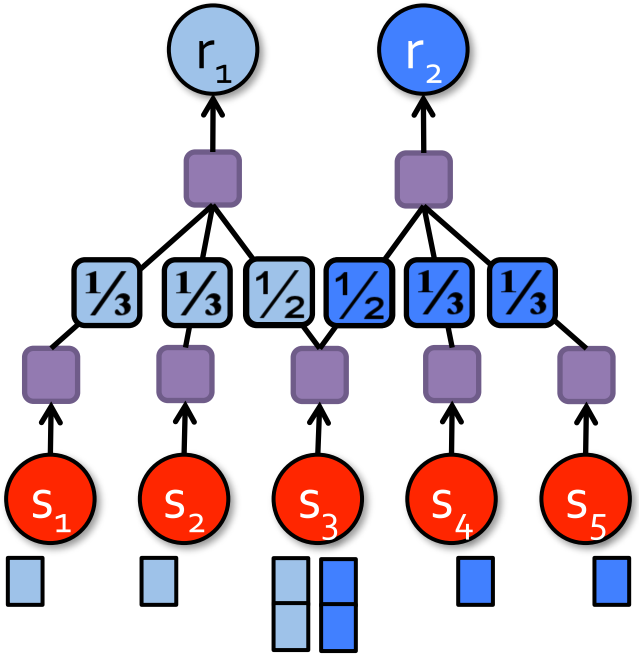




~2x faster than vanilla Cornet

Status quo in Shuffle



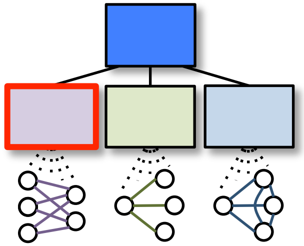


Links to r_1 and r_2 are full: 3 time units

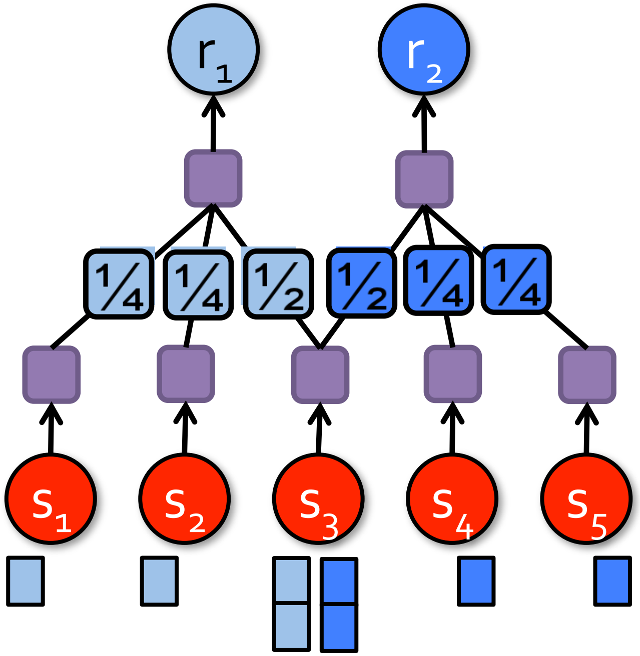
Link from s_3 is full: 2 time units

Completion time: 5 time units

Weighted Shuffle Scheduling



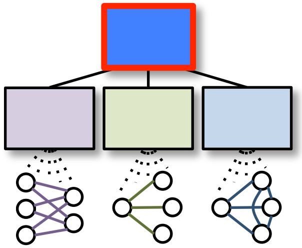
Allocate rates to each flow using weighted fair sharing, where the weight of a flow between a sender-receiver pair is proportional to the total amount of data to be sent



Completion time: 4 time units

Up to 1.5X improvement

Inter-Transfer Controller *aka* Conductor

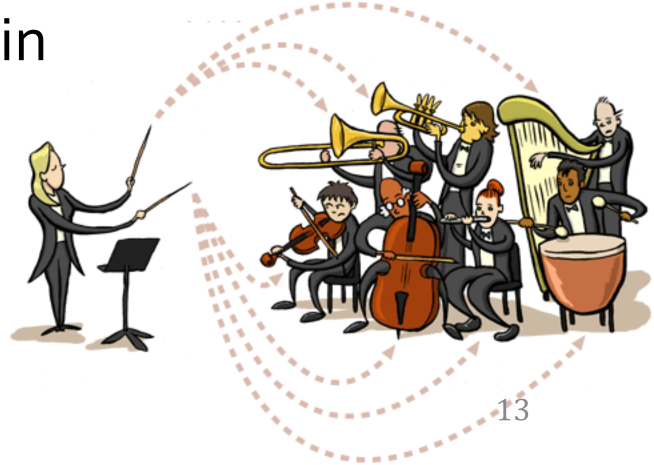


Weighted fair sharing

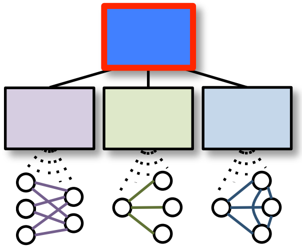
- » Each transfer is assigned a weight
- » Congested links shared proportionally to transfers' weights

Implementation: Weighted Flow Assignment (WFA)

- » Each transfer gets a number of TCP connections proportional to its weight
- » Requires no changes in the network nor in end host OSes



Benefits of the ITC

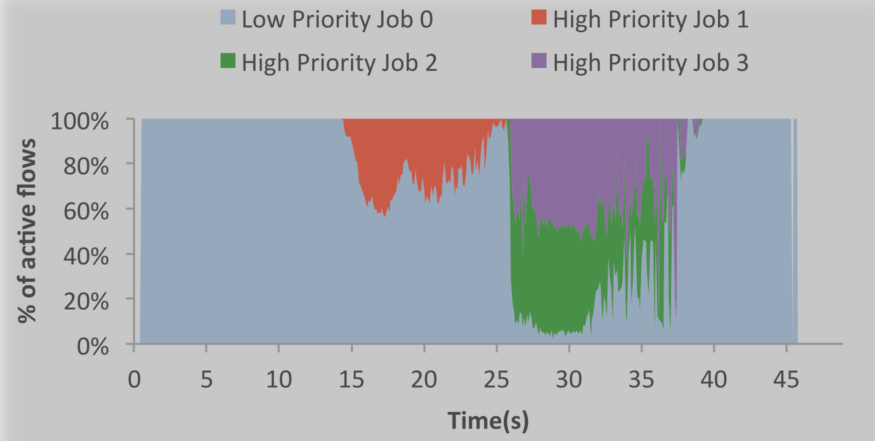


Shuffle using 30 nodes on EC2

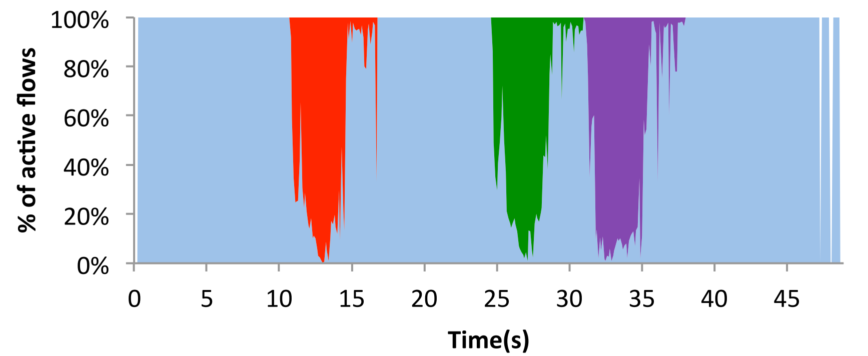
Two priority classes
- » FIFO within each class

Low priority transfer
- » 2GB per reducer

High priority transfers
- » 250MB per reducer



Without Inter-transfer Scheduling



Priority Scheduling in Conductor

43% reduction in high priority xfers
6% increase of the low priority xfer

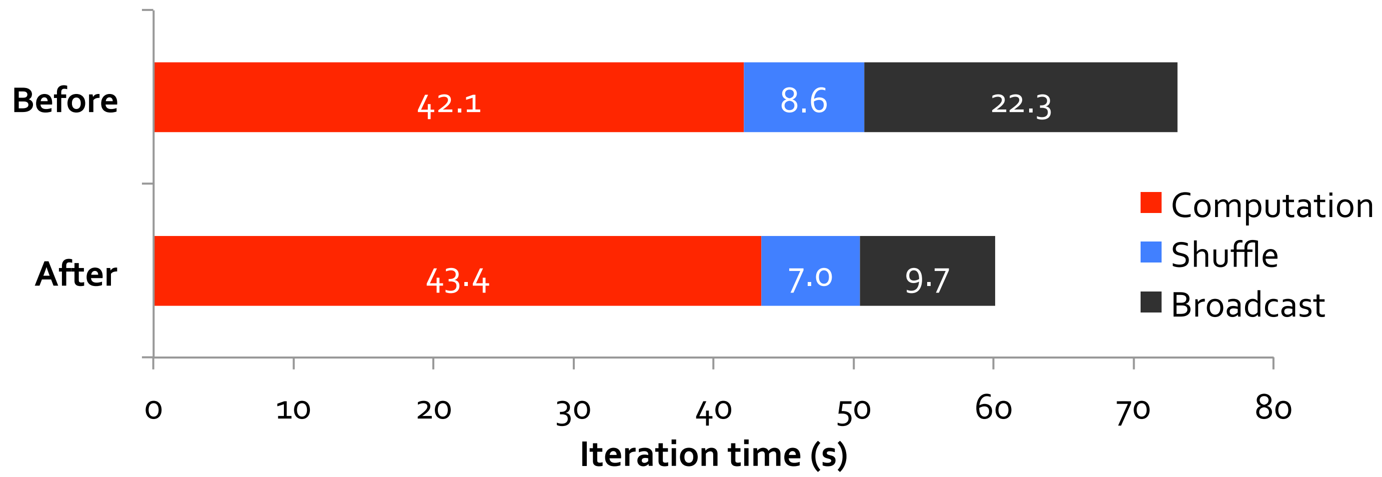
End-to-end evaluation

Developed in the context of Spark – an iterative, in-memory MapReduce-like framework

Evaluated using two iterative applications developed by ML researchers at UC Berkeley

- » Training spam classifier on Twitter data
- » Recommendation system for the Netflix challenge

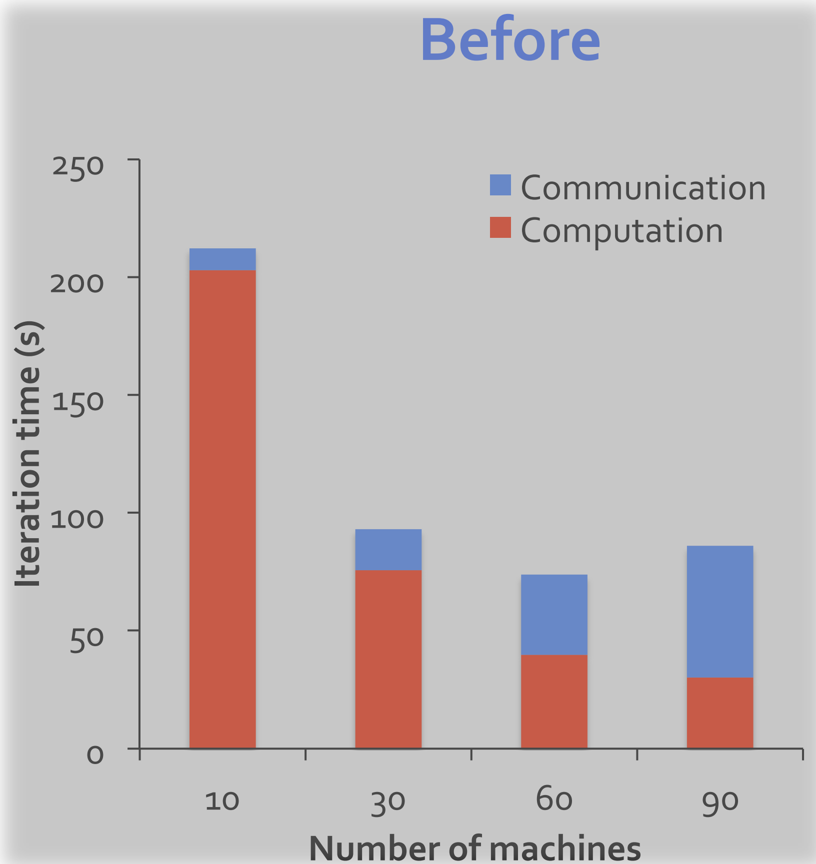
Faster spam classification

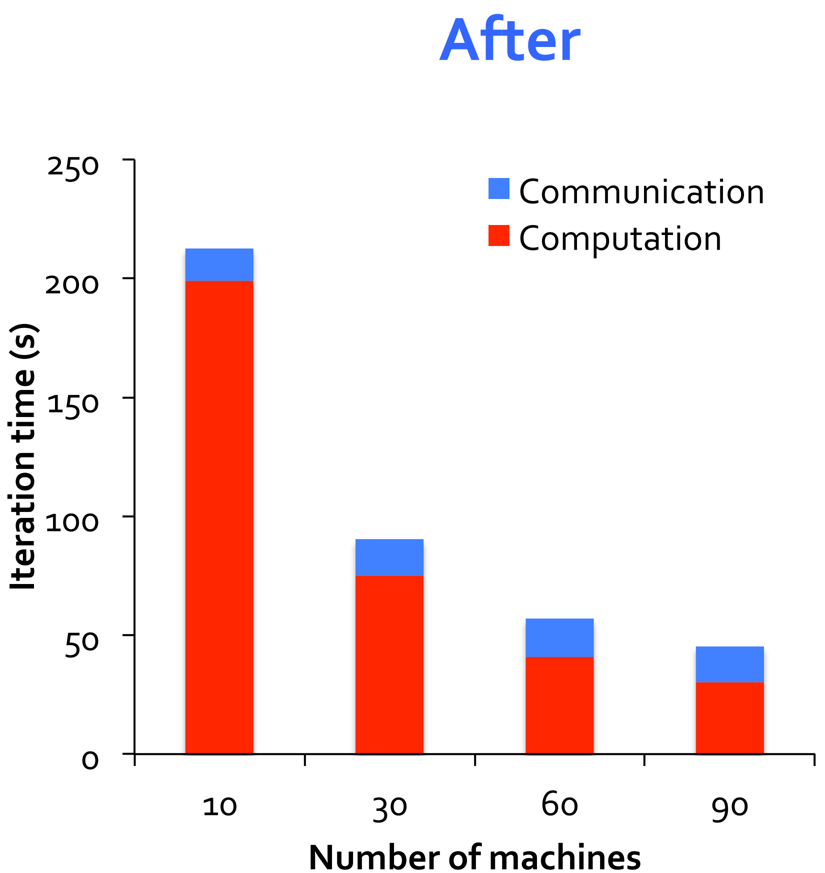


Communication reduced from 42% to 28% of the iteration time

Overall 22% reduction in iteration time

Scalable recommendation system





1.9x faster at 90 nodes

Related work

DCN architectures (VL2, Fat-tree etc.)

» Mechanism for faster network, not policy for better sharing

Schedulers for data-intensive applications (Hadoop scheduler, Quincy, Mesos etc.)

» Schedules CPU, memory, and disk across the cluster

Hedera

» Transfer-unaware flow scheduling

Seawall

» Performance isolation among cloud tenants

Summary

Optimize transfers instead of individual flows

- » Utilize knowledge about application semantics

Coordinate transfers

- » Orchestra enables policy-based transfer management
- » Cornet performs up to 4.5x better than the status quo
- » WSS can outperform default solutions by 1.5x

No changes in the network nor in end host OSes

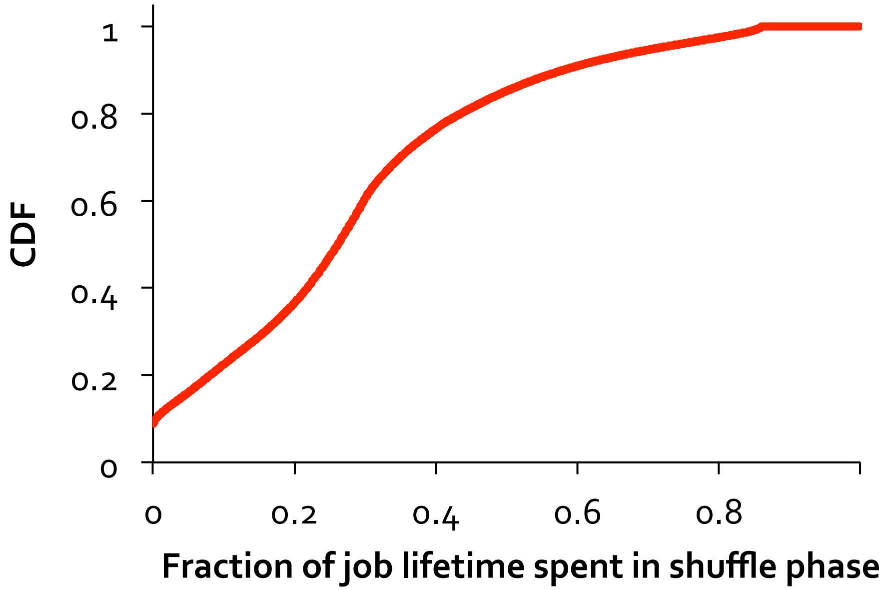
BACKUP SLIDES

MapReduce logs

facebook

Weeklong trace of 188,000 MapReduce jobs from a 3000-node cluster

Maximum number of concurrent transfers is several hundreds



33% time in shuffle on average

Monarch (Oakland'11)

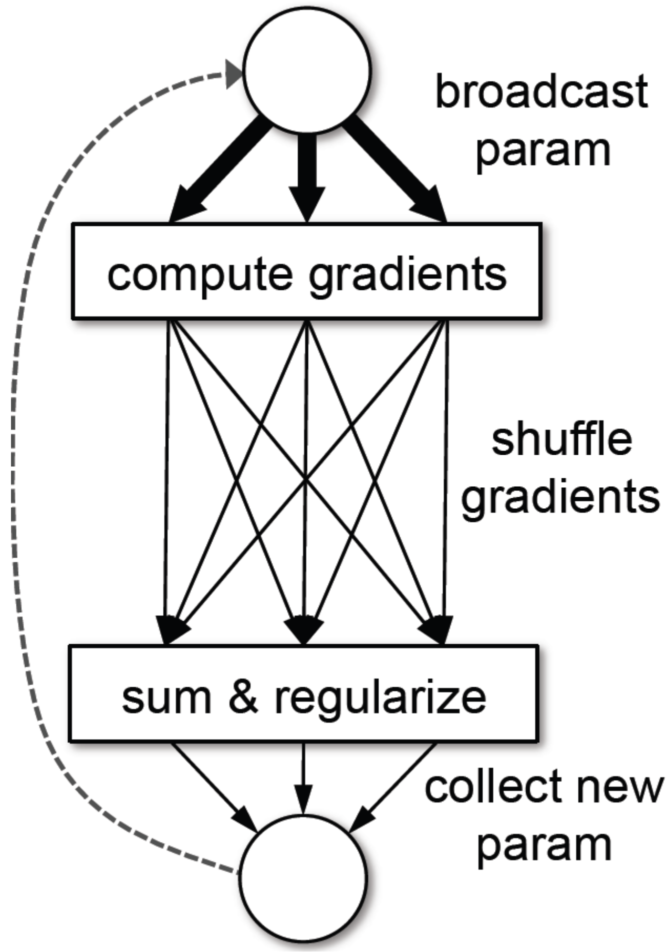
Real-time spam classification from 345,000 tweets with urls

- » Logistic Regression
- » Written in Spark

Spends 42% of the iteration time in transfers

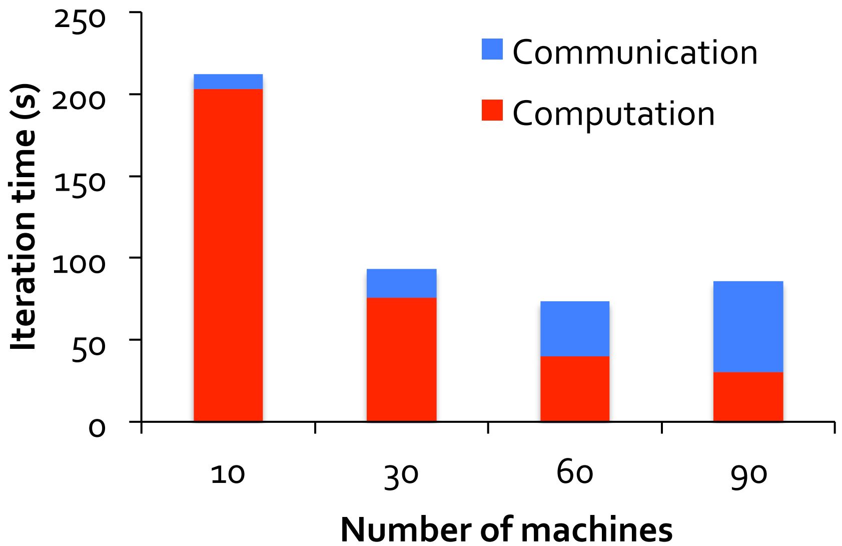
- » 30% broadcast
- » 12% shuffle

100 iterations to converge

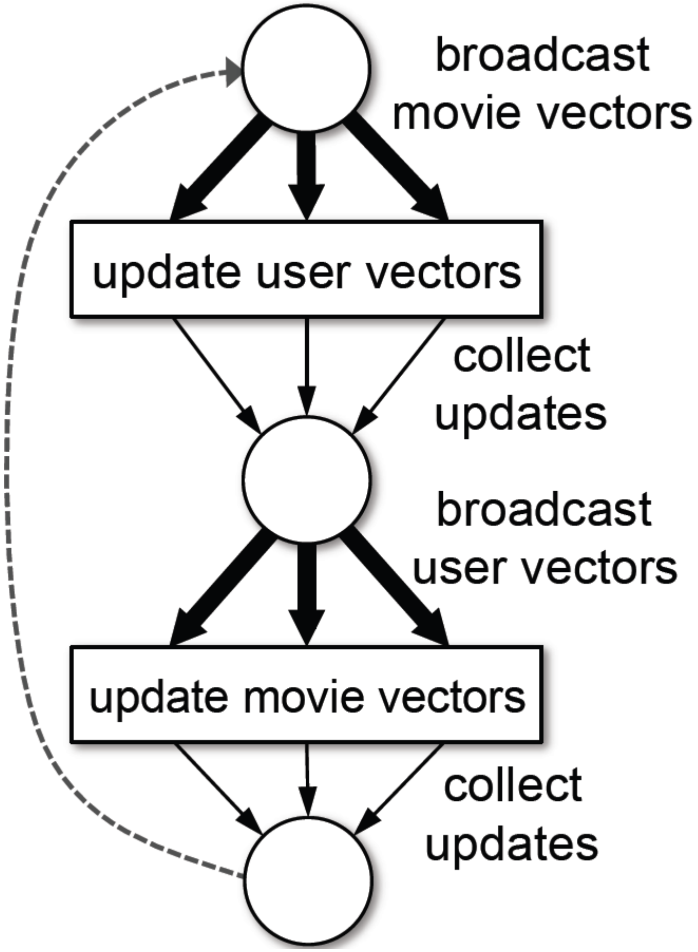


Collaborative Filtering

Does not scale beyond 60 nodes



385MB data broadcasted in each iteration



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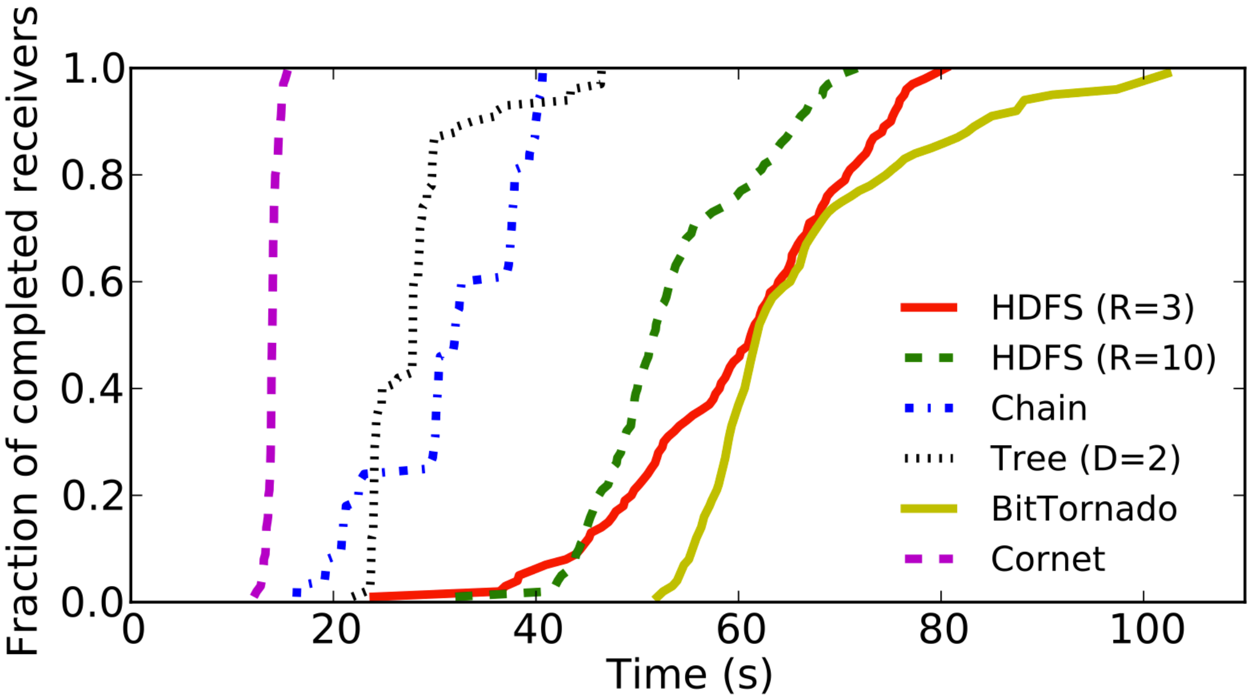
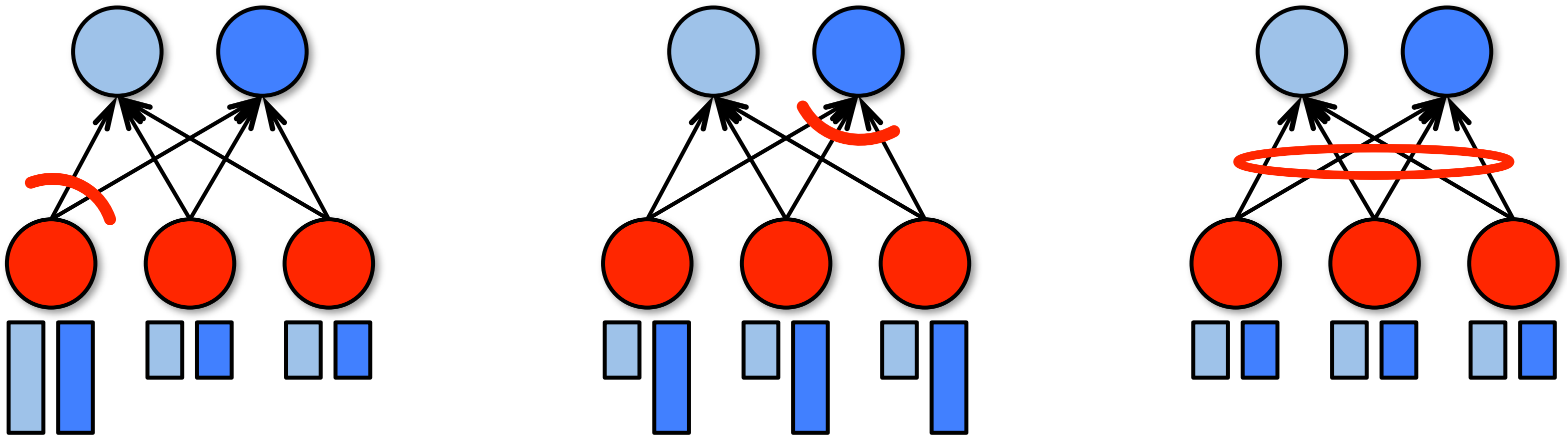


4.5x to 6.5x improvement

Shuffle bottlenecks



At a sender **At a receiver** **In the network**

An optimal shuffle schedule must keep at least one link fully utilized throughout the transfer

Current implementations

Shuffle 1GB to 30 reducers on EC2