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Outline

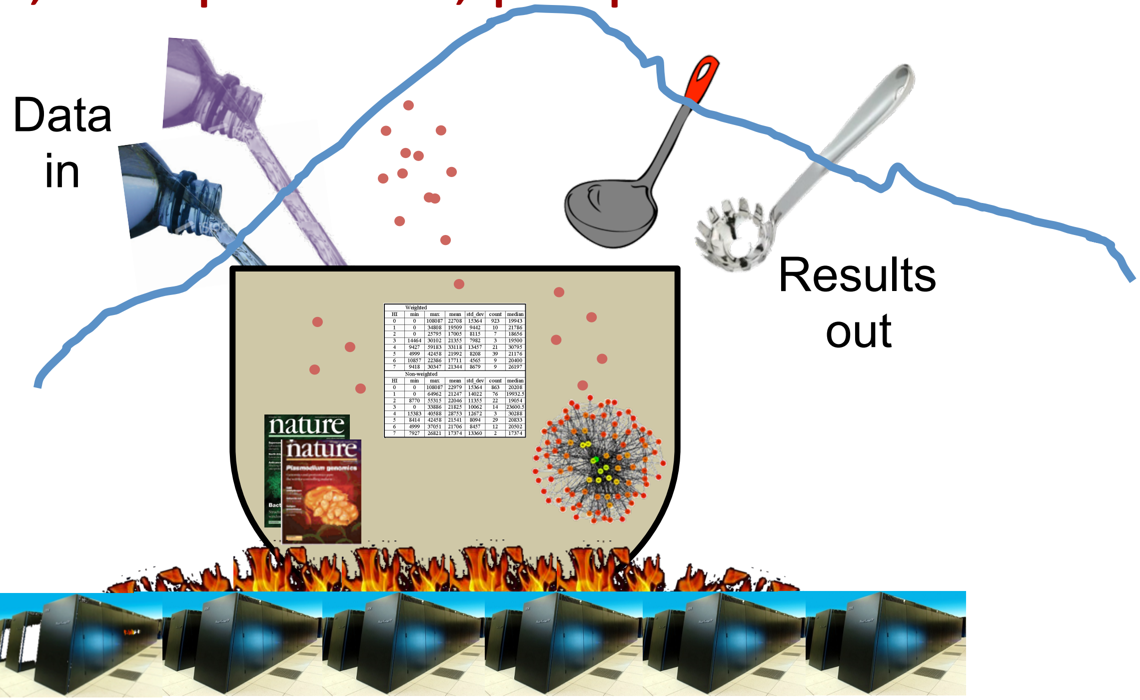
- Motivation: Wide-area Clouds

- Multiple data centers: DMapReduce

- Multiple clouds: Proxy Cloud

Motivation

- Conventional cloud is an attempt to “tame” a distributed world
  - data, computation, people



- Wide-area bottlenecks

The Need

- Make the cloud more “wide-area aware”
  - consider data locality
  - consider end-user locality
  - consider cloud-cloud locality
- How?
  - global multi-data-center services
  - exploit the rich collection of edge computers

Big Data Trend: MapReduce

- Large-Scale Data Processing
  - Want to use 1000s of CPUs on TBs of data

- MapReduce provides
  - Automatic parallelization & distribution
  - Fault tolerance

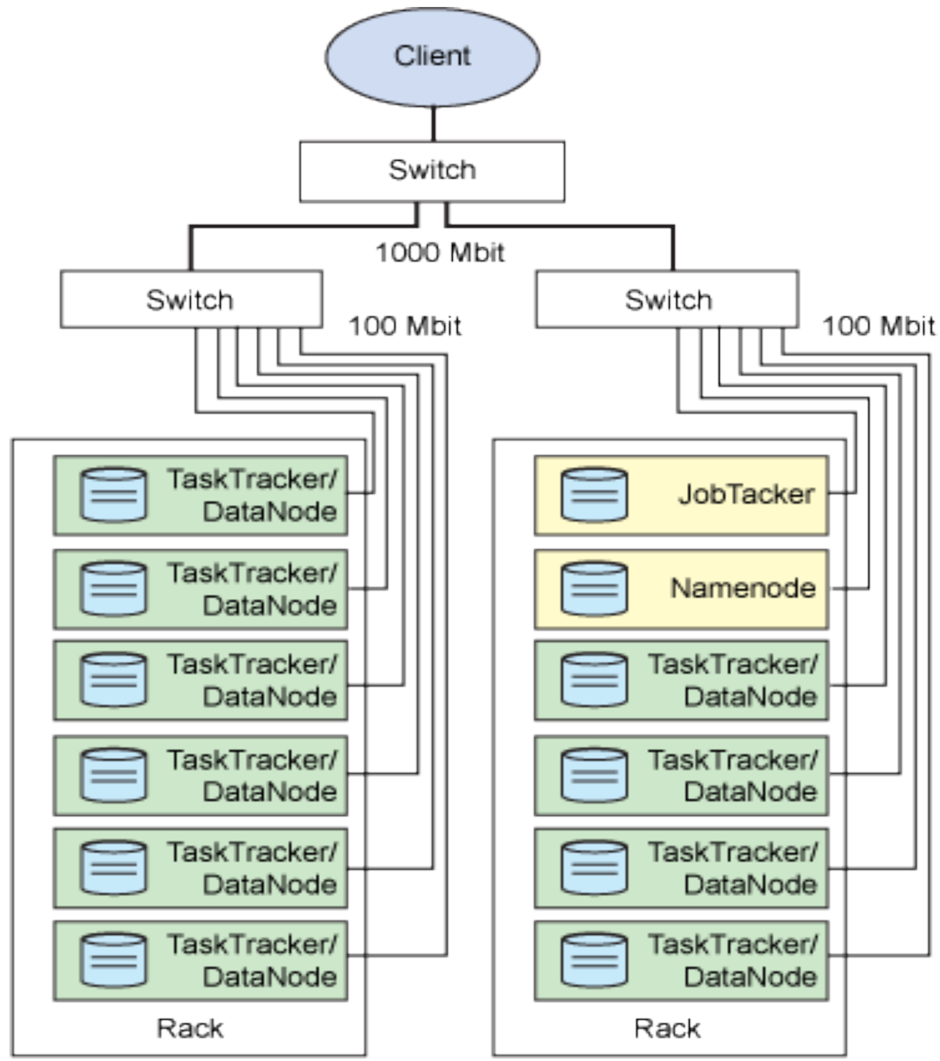
- User supplies two functions:
  - map
  - reduce

Inside MapReduce

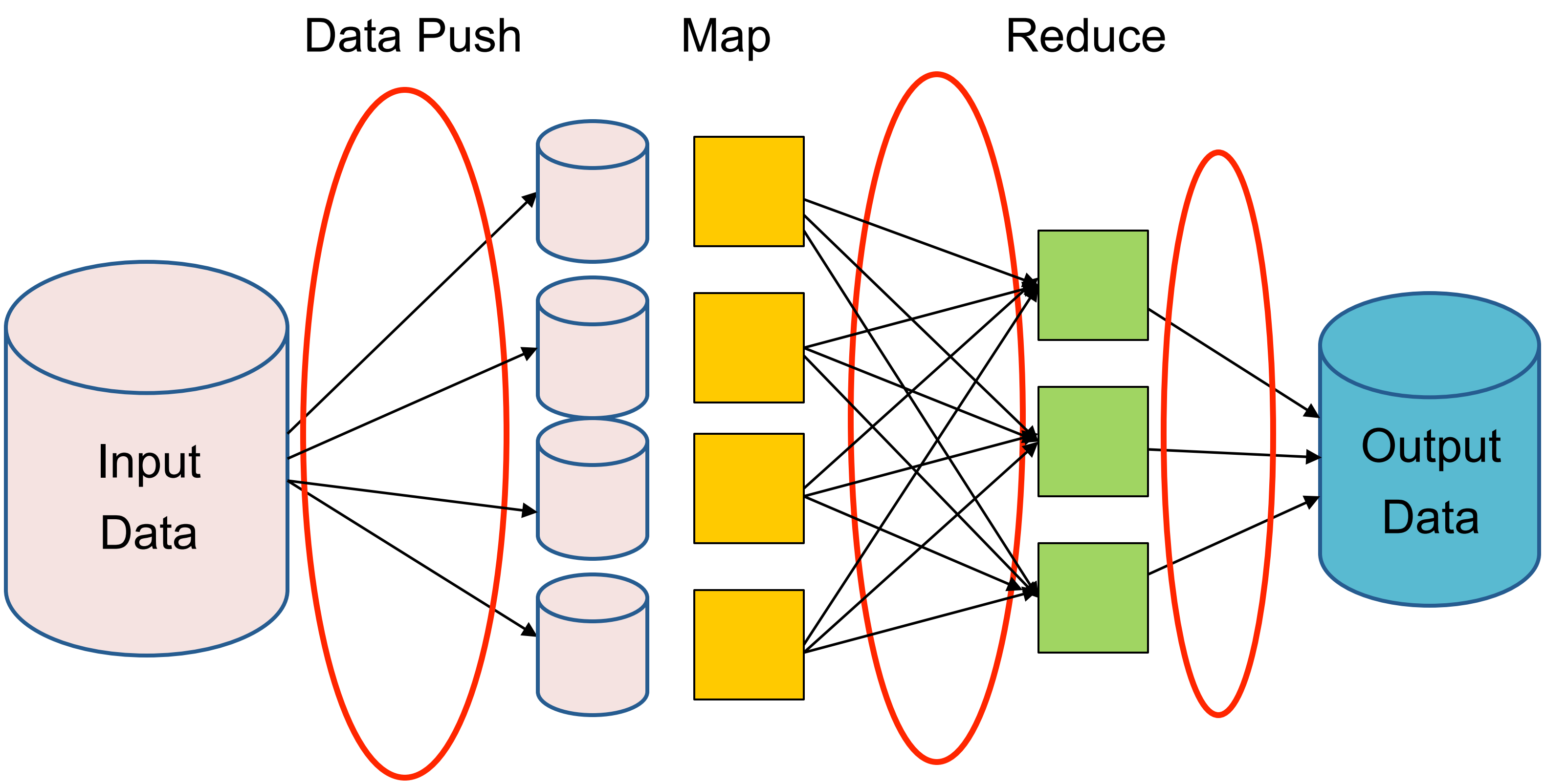
- MapReduce cluster
  - set of nodes N that run MapReduce job
  - specify number of mappers, reducers, <= N
  - master-worker paradigm
- Data set is first injected into DFS
- Data set is chunked (64 MB), replicated three times to the local disks of machines
- Master scheduler tries to run map jobs and reduce jobs on workers near the data

Traditional MapReduce Clusters

- Distributed data
  - Replicated chunks
- Distributed computation
  - Map/reduce tasks
- Assumptions:
  - Data source close to compute nodes
  - Good connectivity



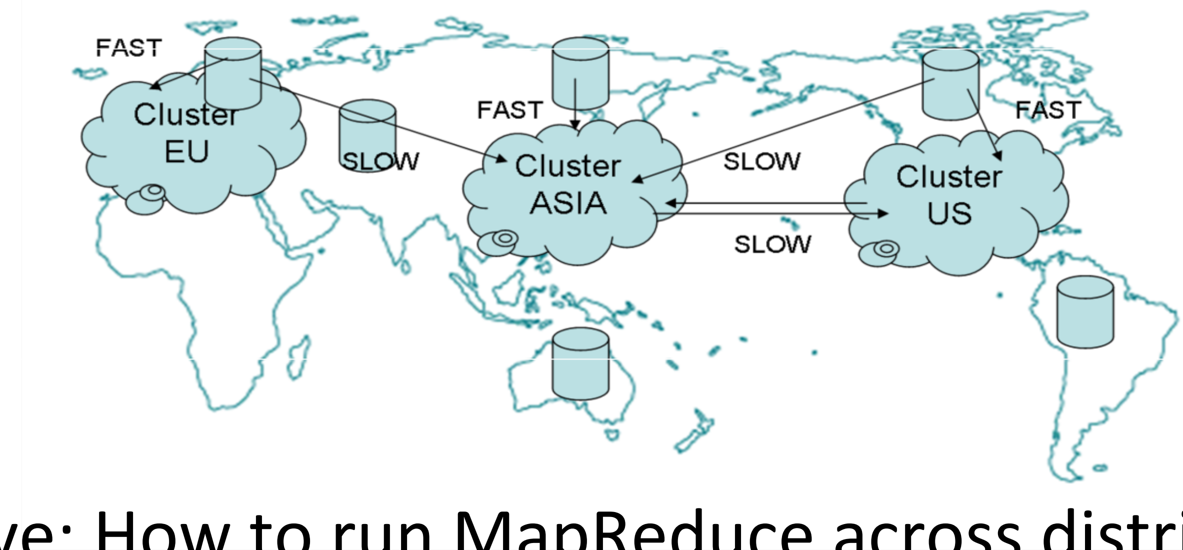
MapReduce Workflow



Lots of Dataflow

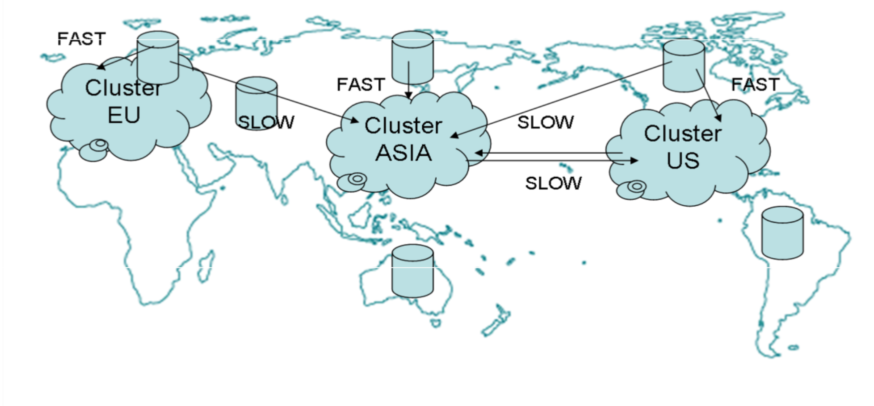
Big Data Trend: Distribution

- Big data is distributed
  - earth science: weather data, seismic data
  - life science: GenBank, NCI BLAST, PubMed
  - health science: GoogleEarth + CDC pandemic data
  - web 2.0: user multimedia blogs

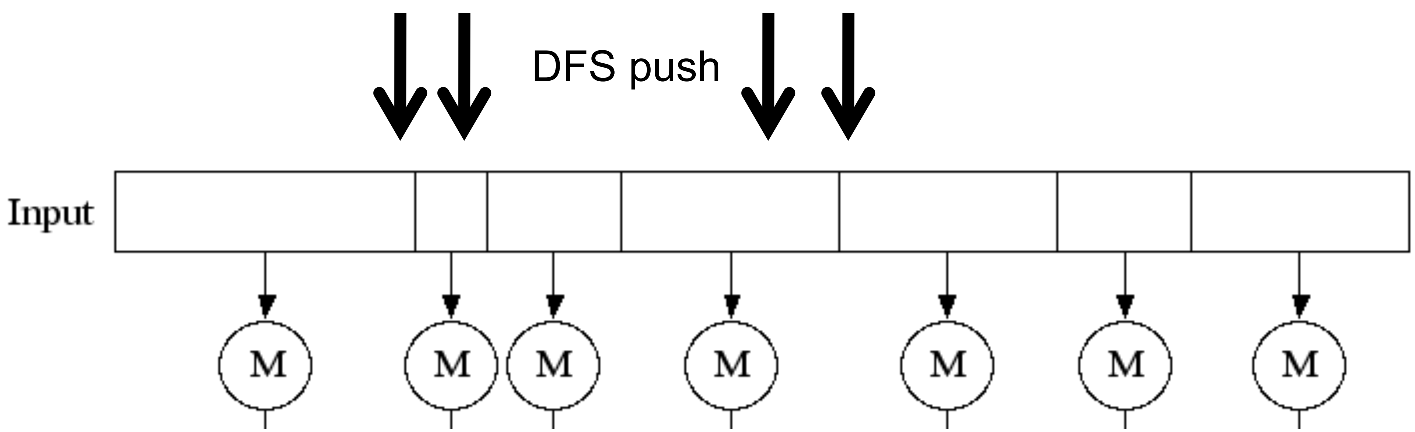


Objective: How to run MapReduce across distributed data?

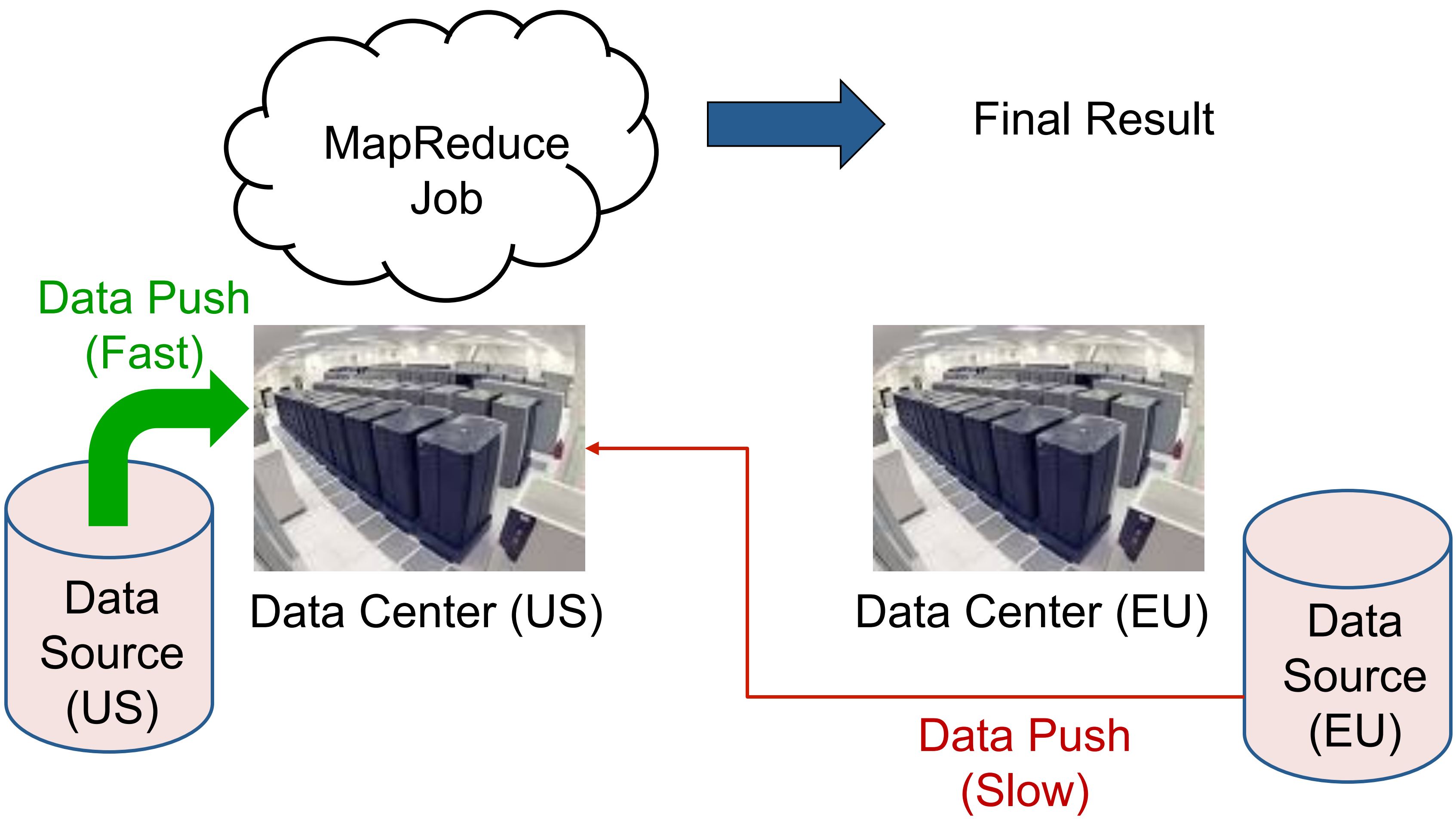
Wide-Area MapReduce



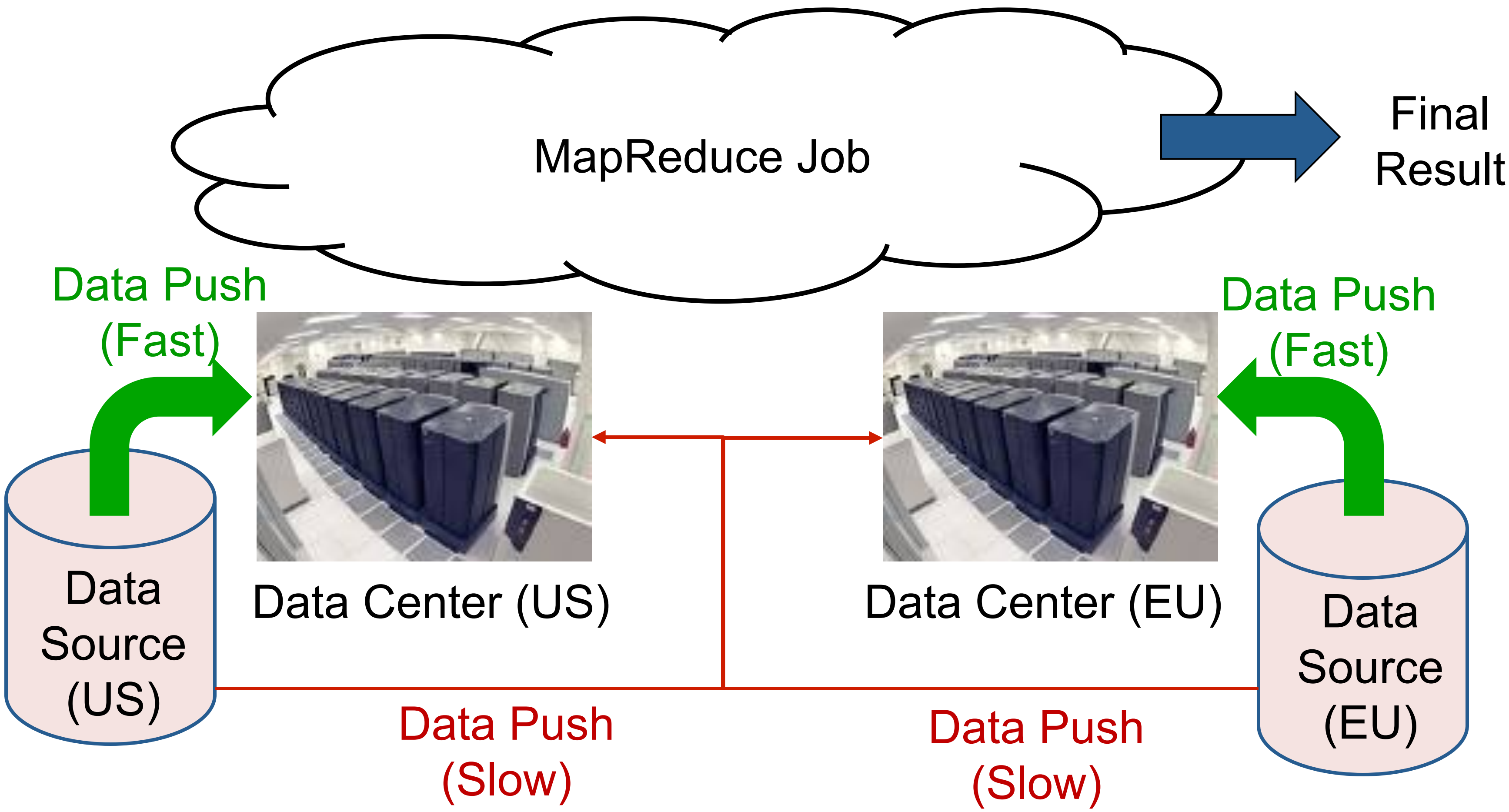
- Data in different data-centers
- Run MapReduce across them
- Data-flow spanning wide-area networks



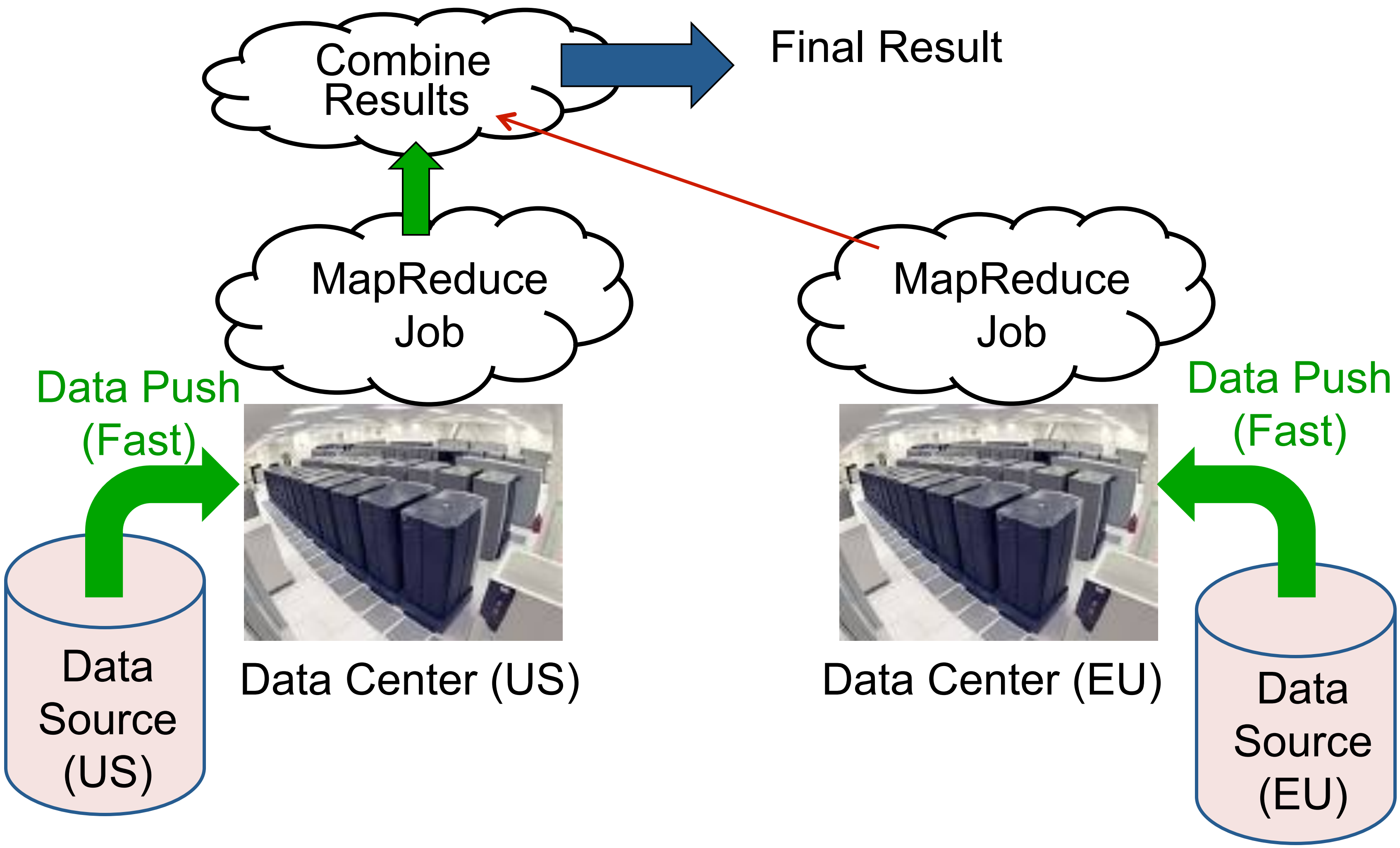
Option 1: Local MapReduce



Option 2: Global MapReduce



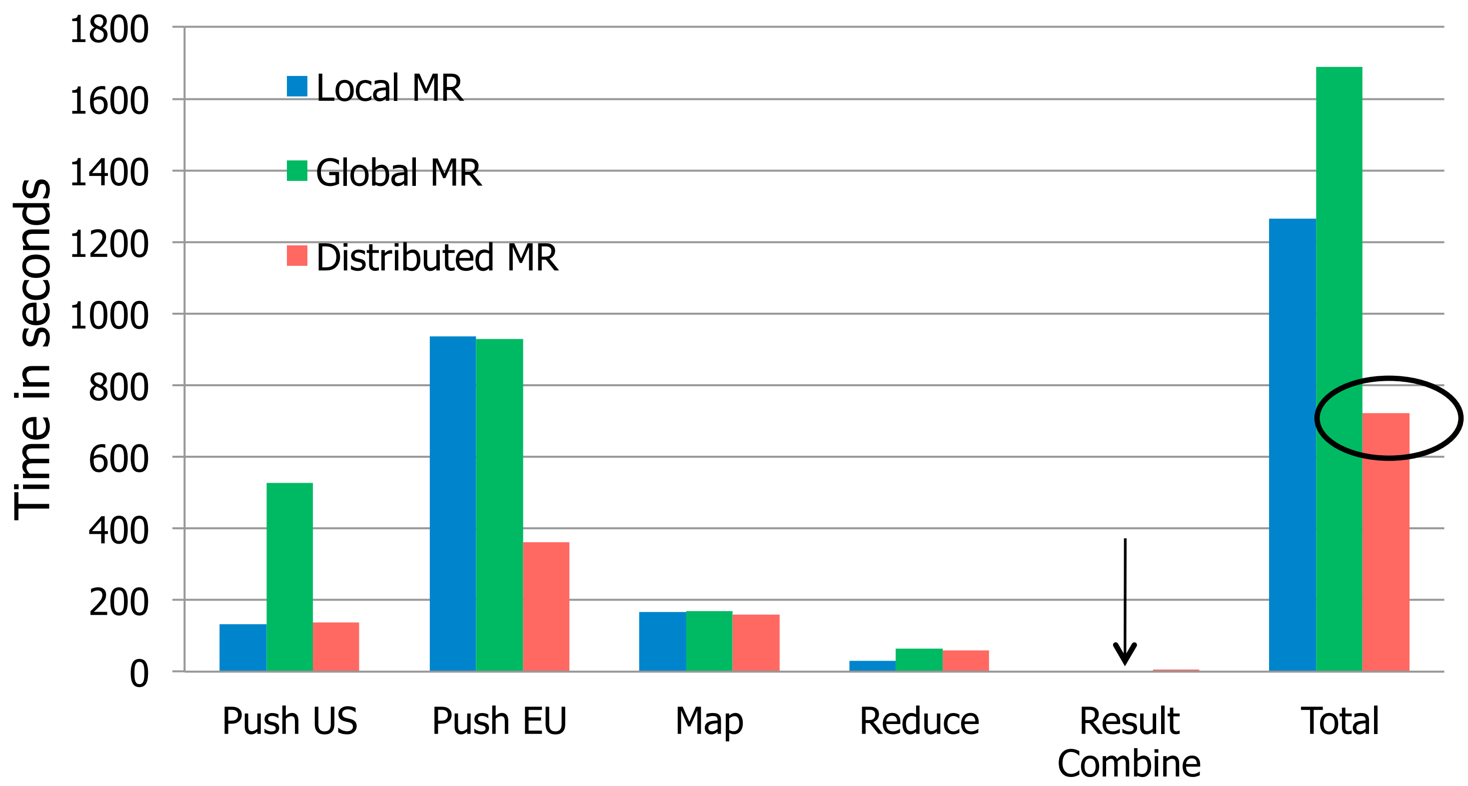
Option 3: Distributed MapReduce



Experimental Setup

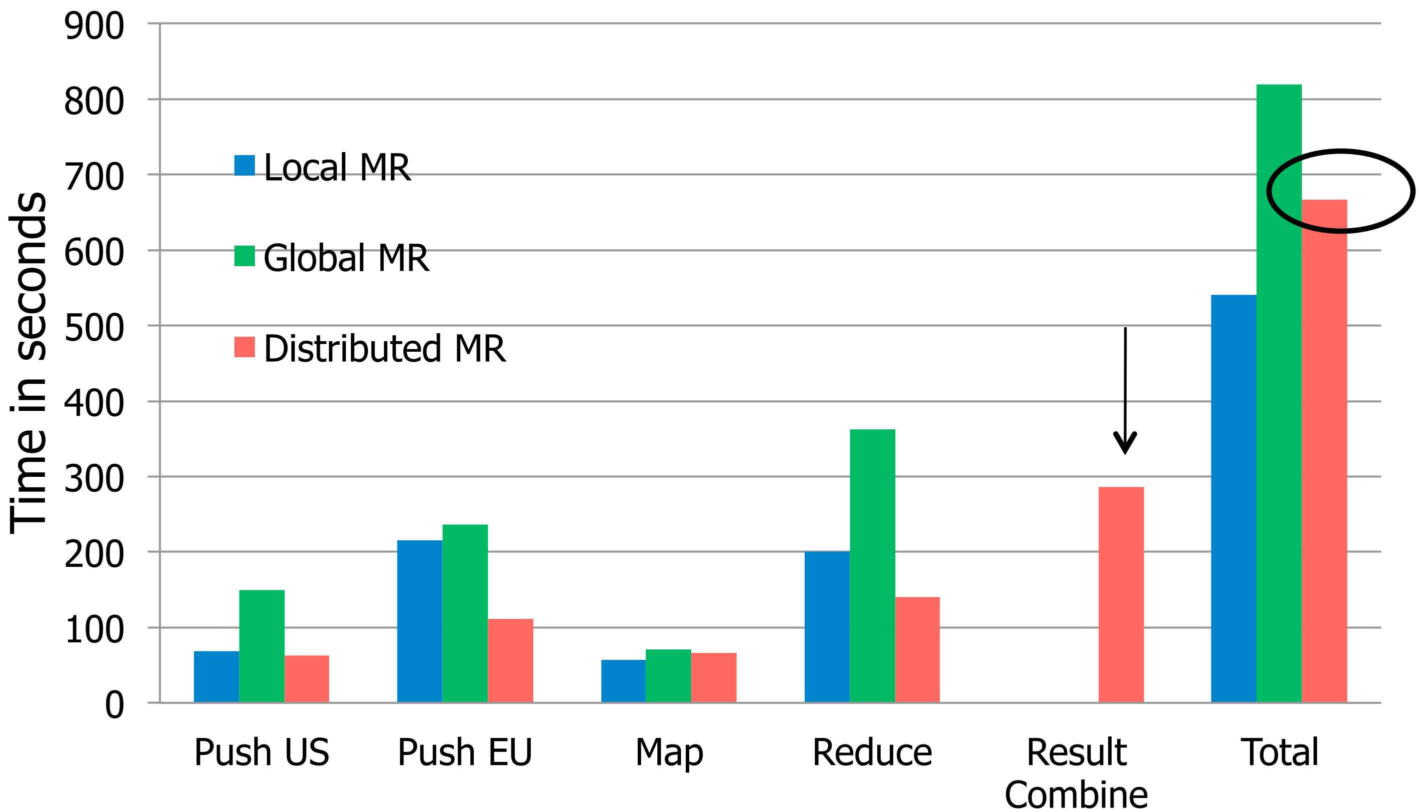
- PlanetLab: 4 US, 4 EU nodes
- Amazon EC2: 3 US, 3 EU small instances
- Benchmarks:
  - Word count with text data: High compression
    - 800 MB PLab, 3.2 GB EC2
  - Word count with random data: Ballooning
    - 250 MB PLab, 1 GB EC2
  - Sort with random data: No aggregation
    - 250 MB PLab, 1 GB EC2

PlanetLab: WordCount (text data)



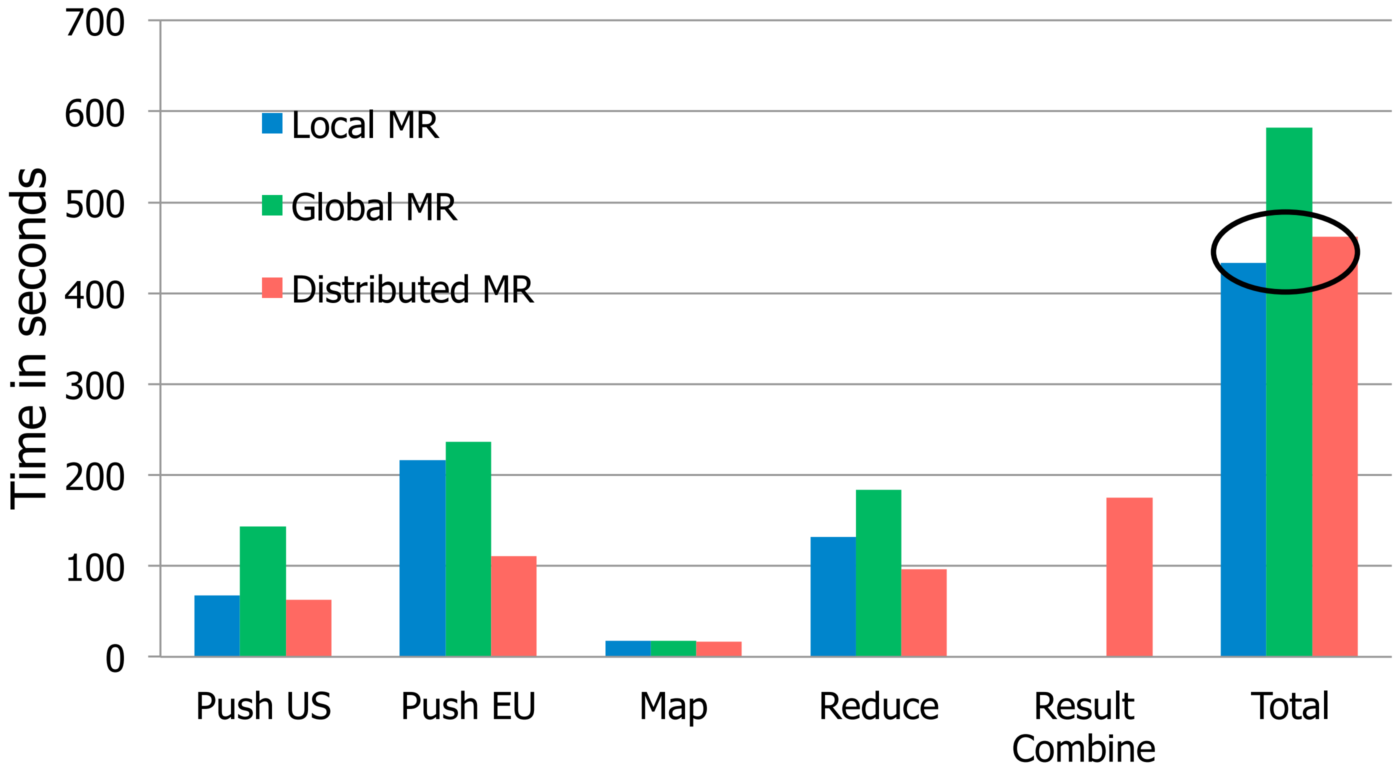
- Distributed MR works best in presence of data compression

PlanetLab: WordCount (random data)



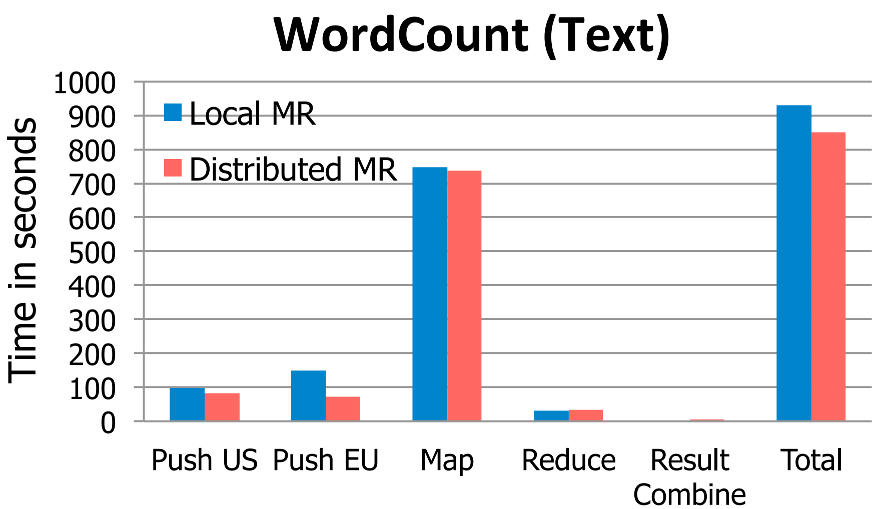
- Local MR works best in presence of data ballooning

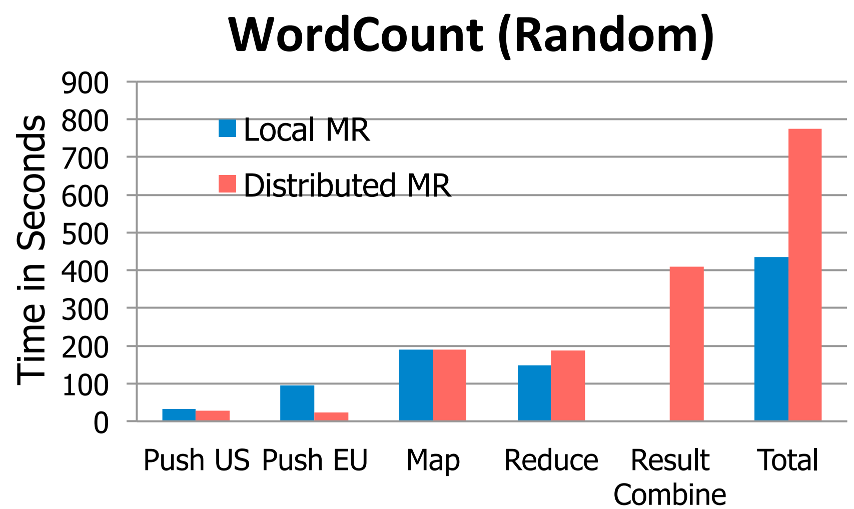
PlanetLab: Sort

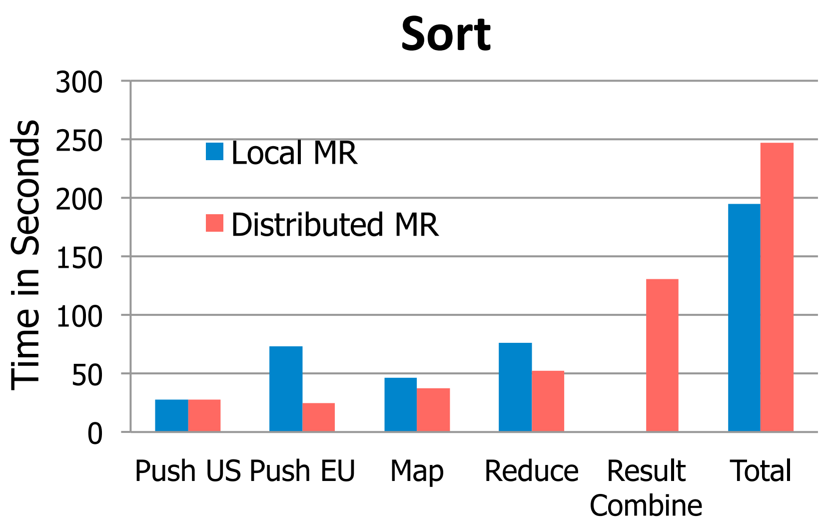


- Similar performance in presence of “equal” data

EC2 Results


WordCount (Text)
Time in seconds
1000
900
800
700
600
500
400
300
200
100
0
Local MR
Distributed MR
Push US
Push EU
Map
Reduce
Result Combine
Total


WordCount (Random)
Time in Seconds
900
800
700
600
500
400
300
200
100
0
Local MR
Distributed MR
Push US
Push EU
Map
Reduce
Result Combine
Total


Sort
Time in Seconds
300
250
200
150
100
50
0
Local MR
Distributed MR
Push US
Push EU
Map
Reduce
Result Combine
Total

Observations

- Amount of data compression is a critical factor
  - High compression => avoid initial data push cost
  - High ballooning => avoid result combine cost

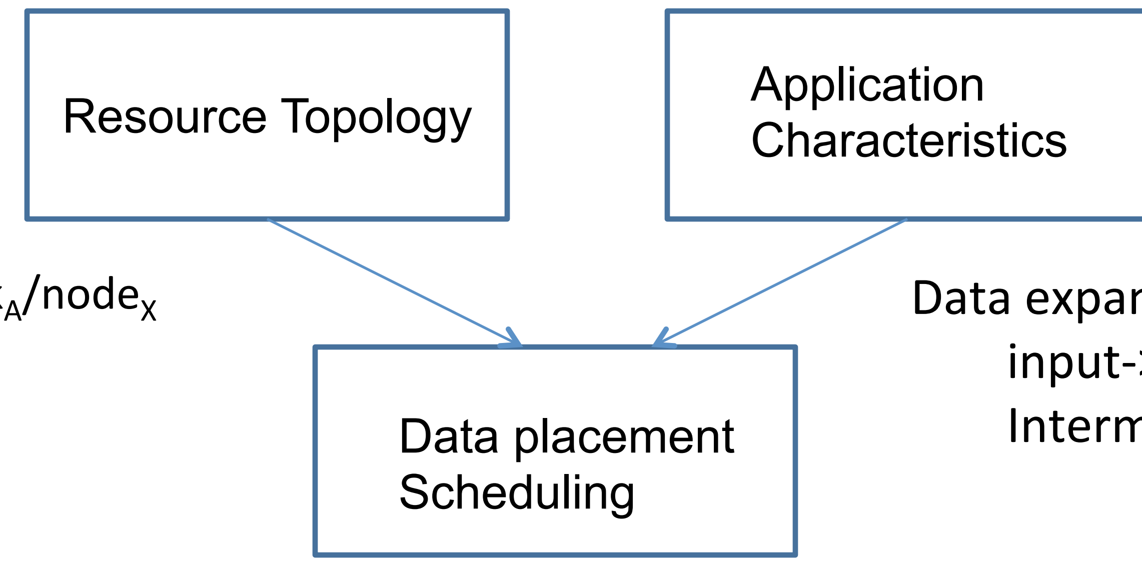
- Make MapReduce topology-aware
  - Data push should consider locality
  - Task scheduling should consider co-placed execution

Global MR

- Skew in data sizes at each site
- Uneven compute resources in different DCs
  - Can be useful in presence of heterogeneity, failures
- Is a generalization of Local MR and Distributed MR

Intelligent Data Placement

- HDFS push
  - local node, same rack, random rack



$/DC_i/rack_A/node_X$

Data expansion factors

input->intermediate, α

Intermediate->output, β

select LMR, DMR, GMR

Generalize beyond HDFS/MapReduce!

Proxy Cloud

Cloud landscape: Diversity and Specialization

- Data clouds
  - S3, SkySurvey, GoogleHealth
- Compute clouds
  - EC2, IronScale
- Service clouds
  - Gmail, Gmaps, Google-earth
- Specialization
  - Non-functional: security, reliability, SLAs, cost

Confluence

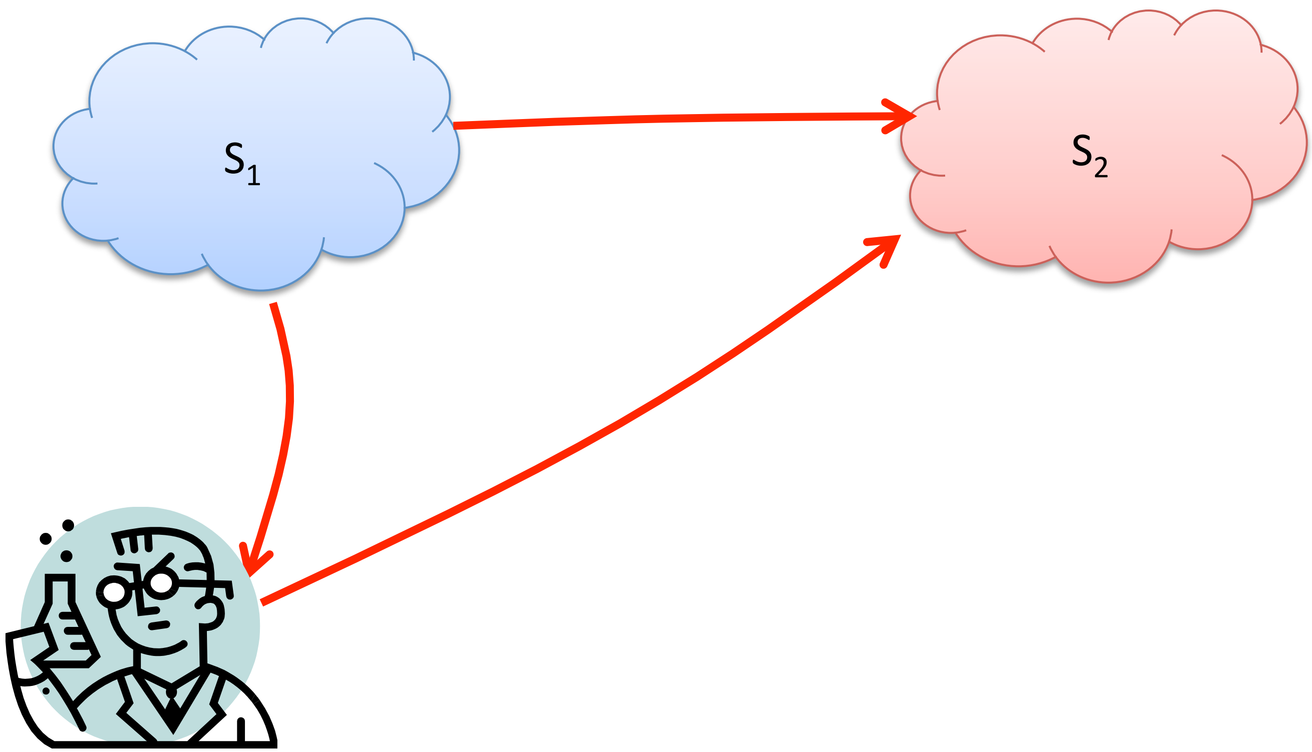
- Cloud diversity and specialization =>
  - (1) No single cloud model will rule
  - (2) New distributed models are attractive
  - (3) Emerging applications will utilize multiple clouds “multi-cloud” applications

Multi-Cloud Applications

- Distributed data mining
  - Ex: weather data + commodity prices
- Scientific workflows
  - Ex: life science: GenBank<->BLAST<->PubMed, …
- Mashups
  - Ex: GoogleEarth + CDC pandemic data
- Multi-cloud/DC parallel frameworks
  - Ex: MapReduce

The Problem

- Cloud-cloud bottlenecks
- User-cloud bottlenecks

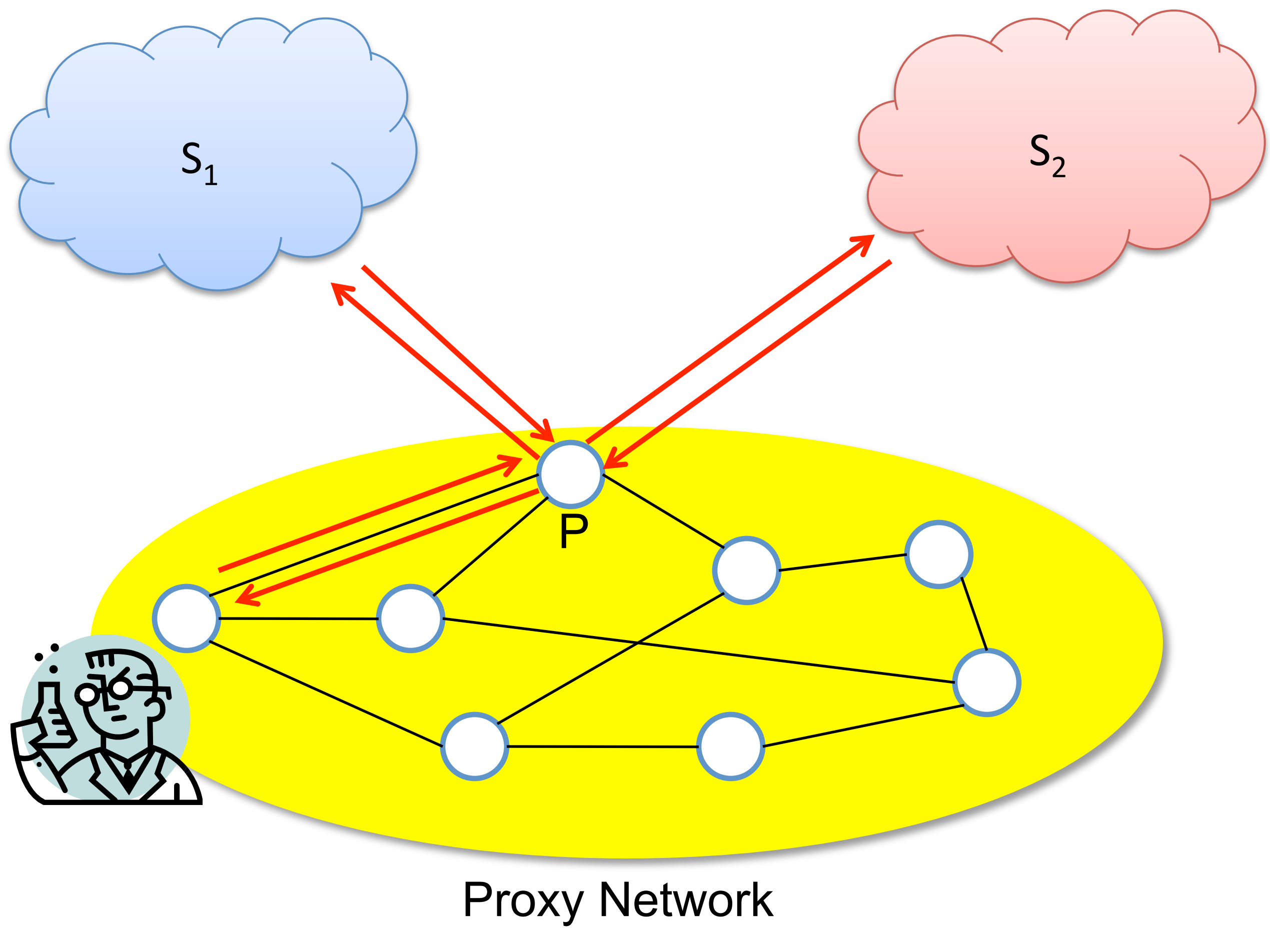


Multiple Clouds: Proxy Cloud

- Using edge nodes with the commercial cloud(s)

- Goal to provide
  - cloud <-> cloud locality
  - cloud <-> end-user locality
  - cloud- <-> data locality

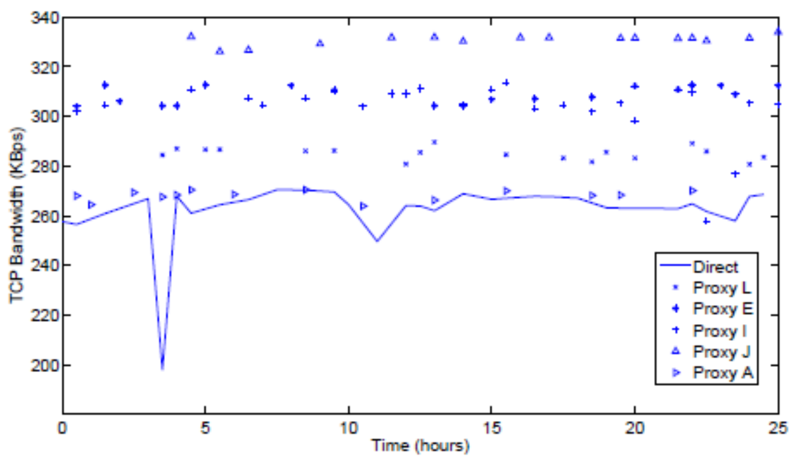
Solution: Proxy Architecture: 50K ft



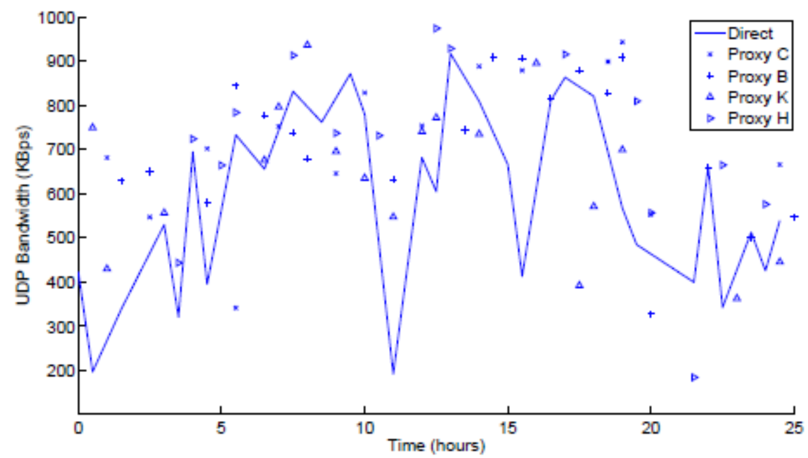
Proxy Roles

- Cloud service interaction
  - Proxy as a client
- Routing
  - Proxy routes data to other proxies
- Computing => Grids
  - Proxy computes data operators: compress, filter, merge, mine, …
- Caching => P2P
  - Proxy caches data (from cloud, computations, …)

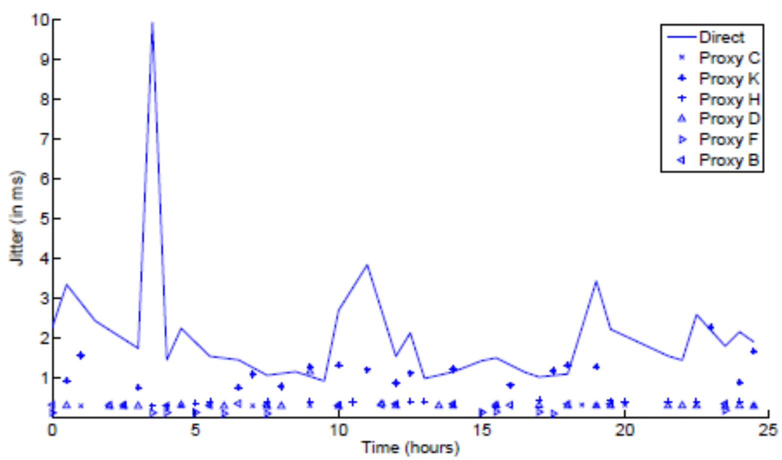
Networking Benefits



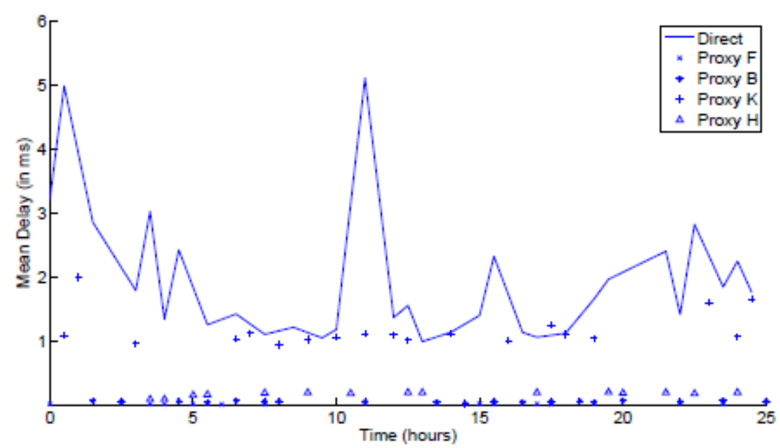
(a) TCP bandwidth (KBps) (Higher is better)



(b) UDP bandwidth (KBps) (Higher is better)

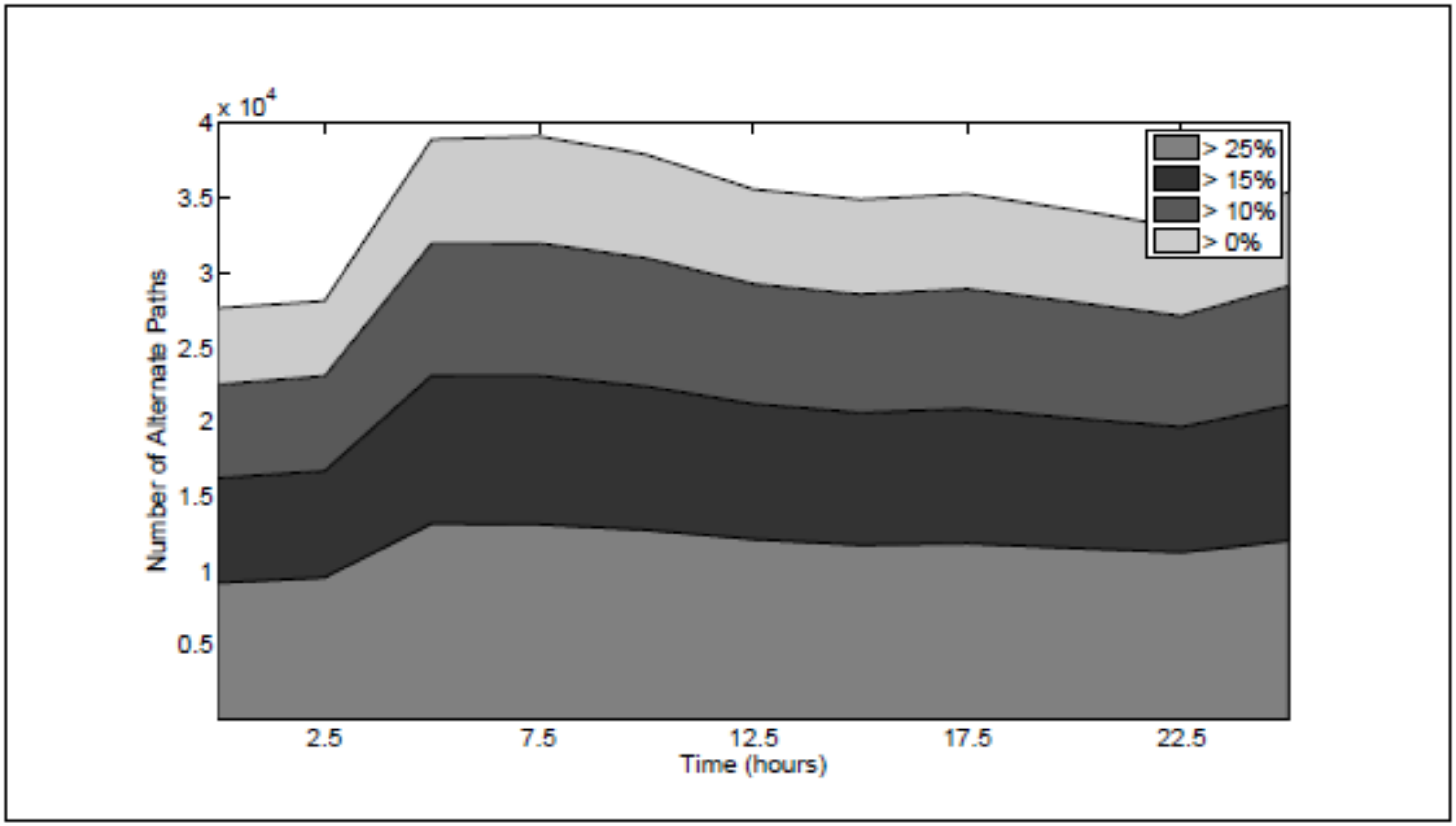


(c) UDP delay (ms) (Lower is better)

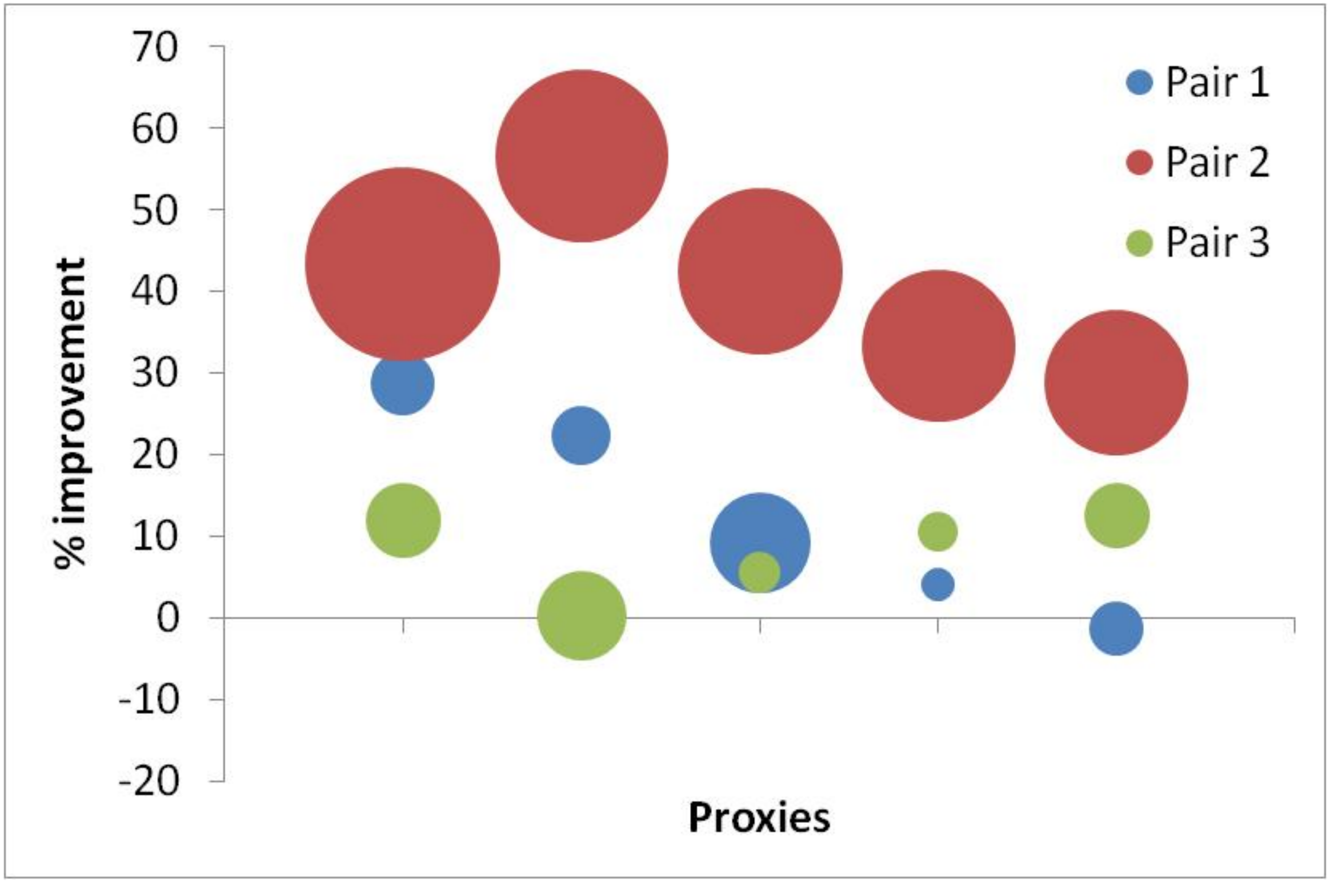


(d) UDP jitter (ms) (Lower is better)

Many better data paths …



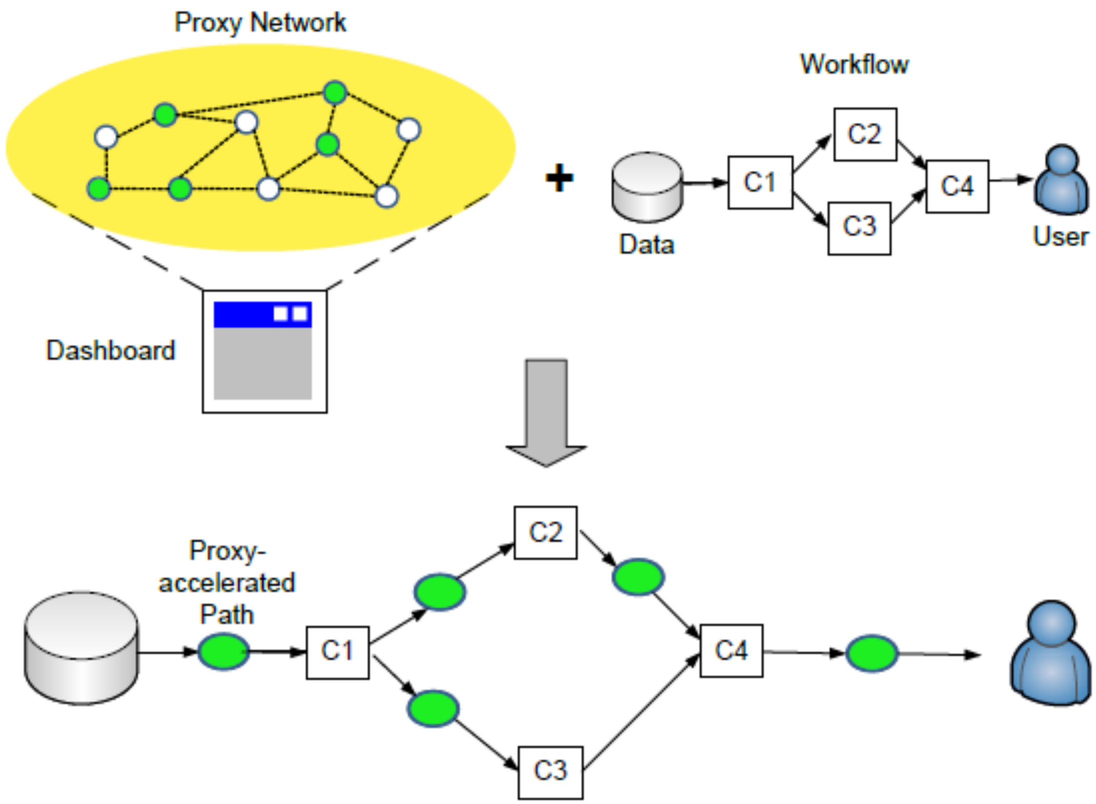
Some acceleration is large …



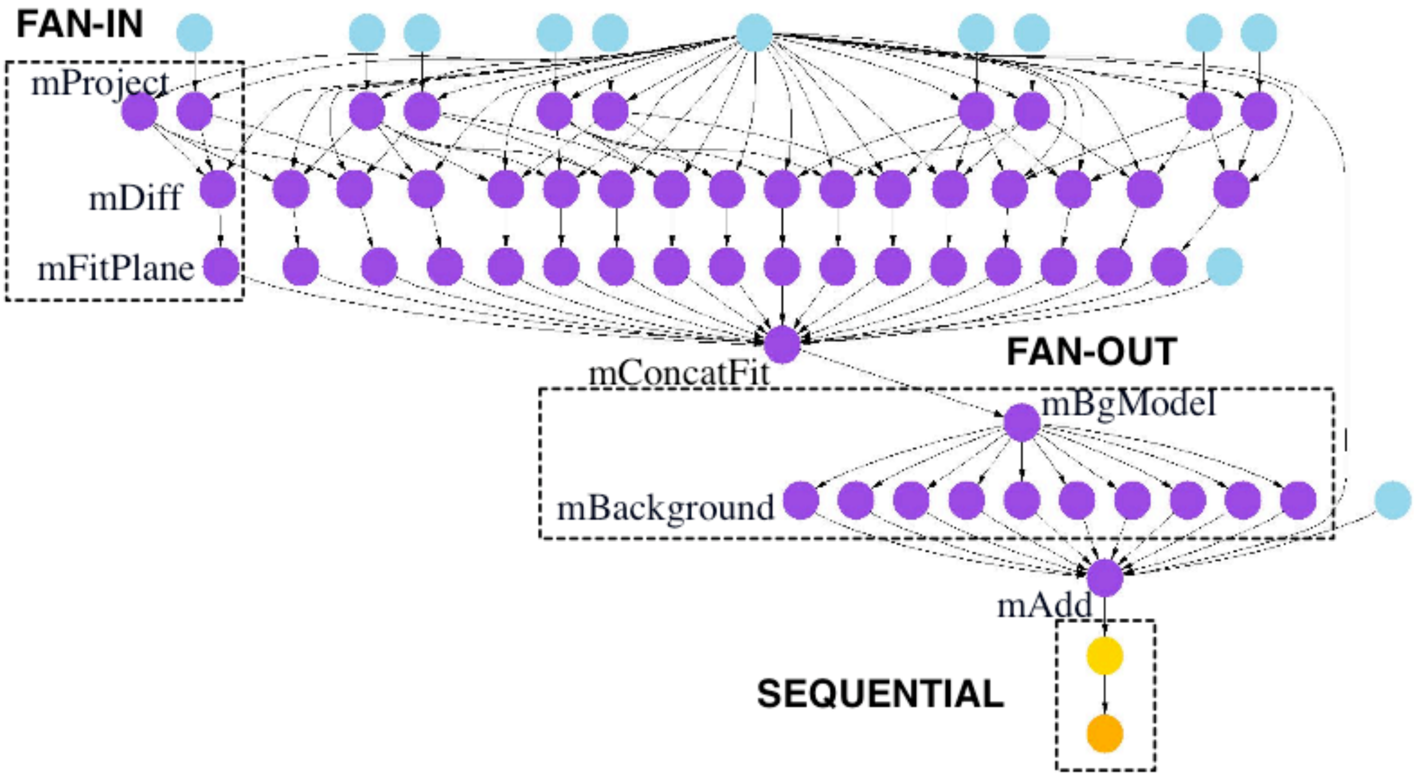
How do we get this information?

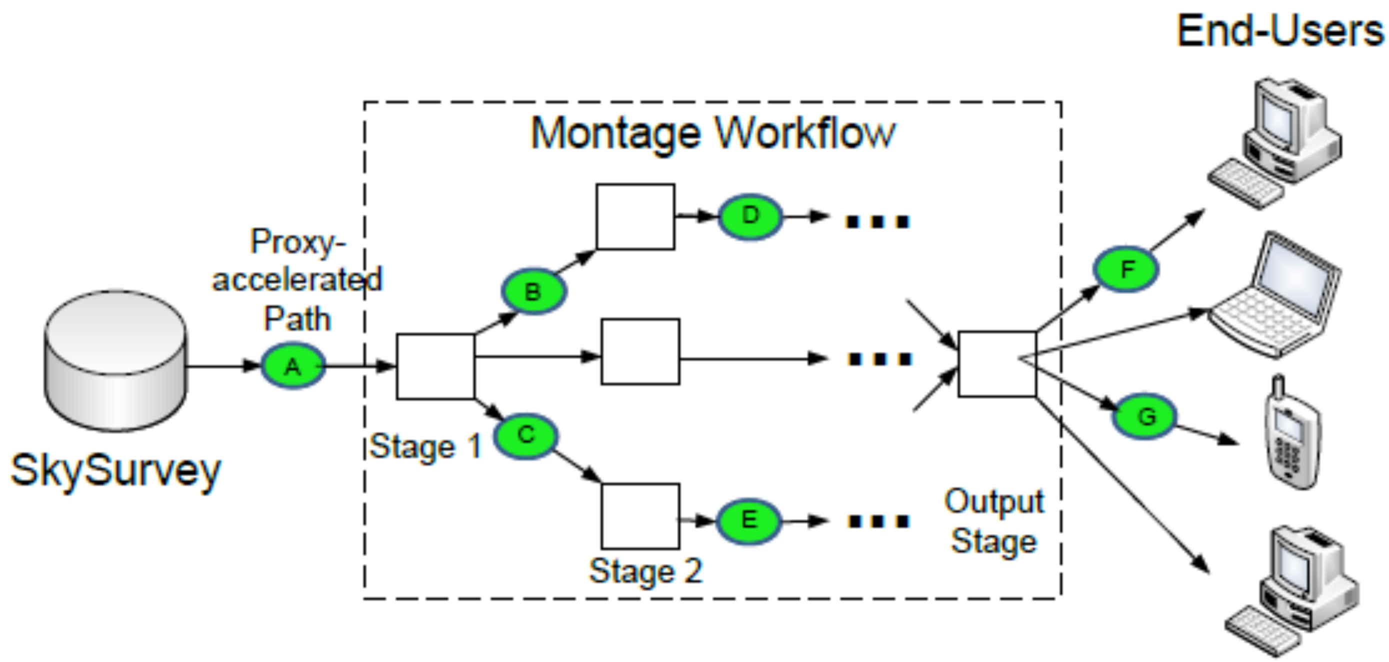
Network dashboard: netstat.cs.umn.edu

Workflow Acceleration



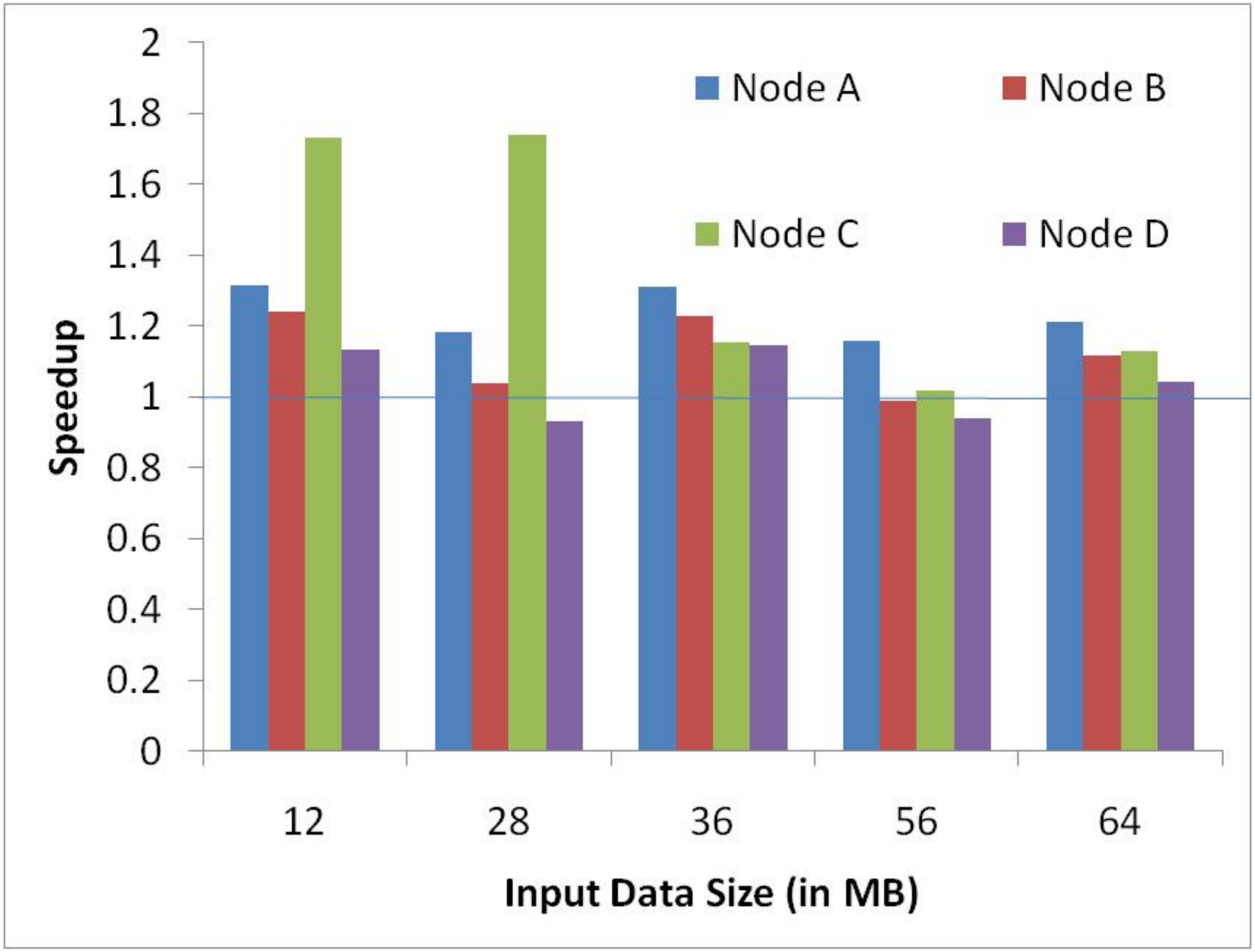
Example: Montage





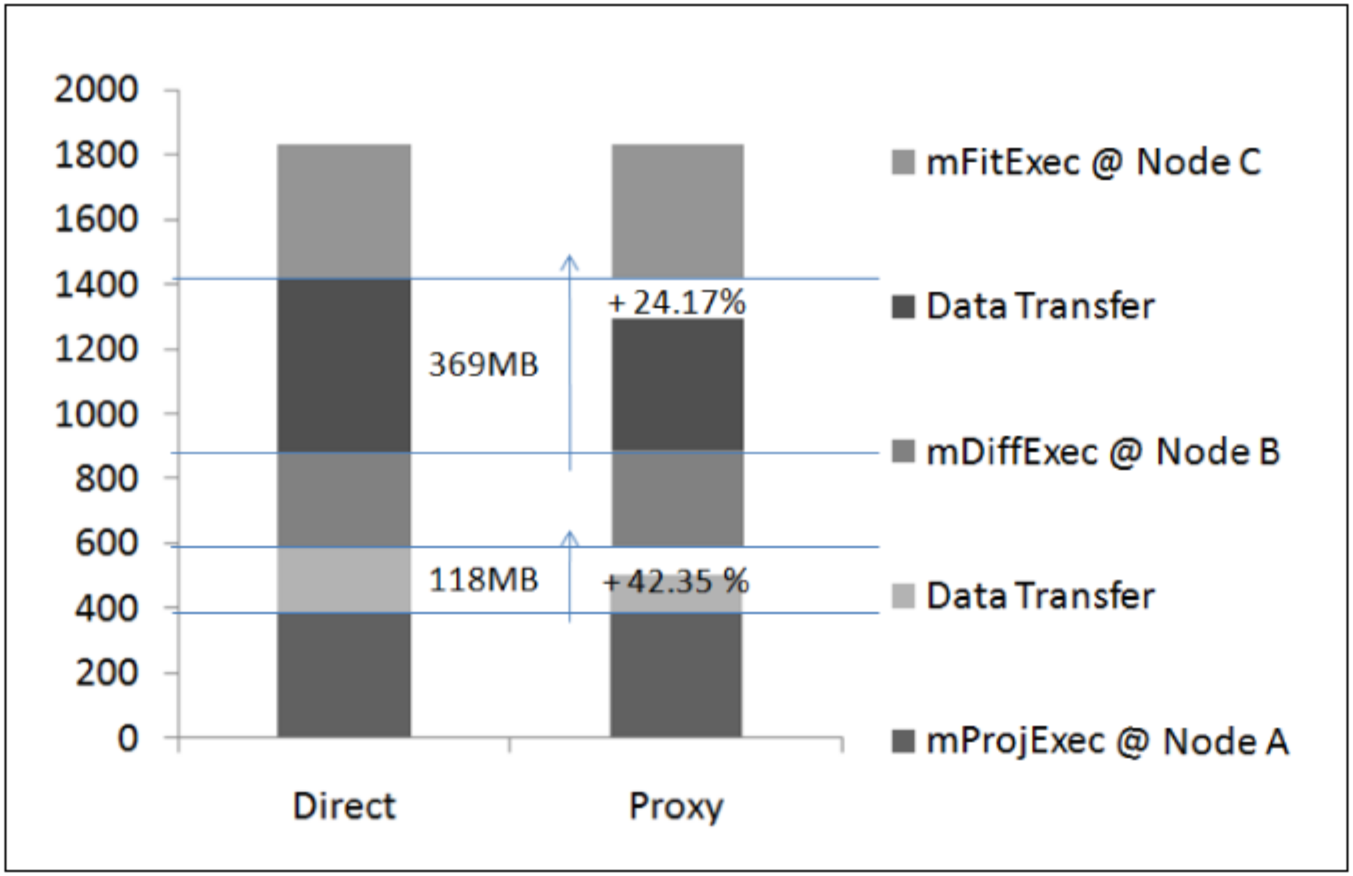
A-E communication role
F-G computation role

From data server to compute node

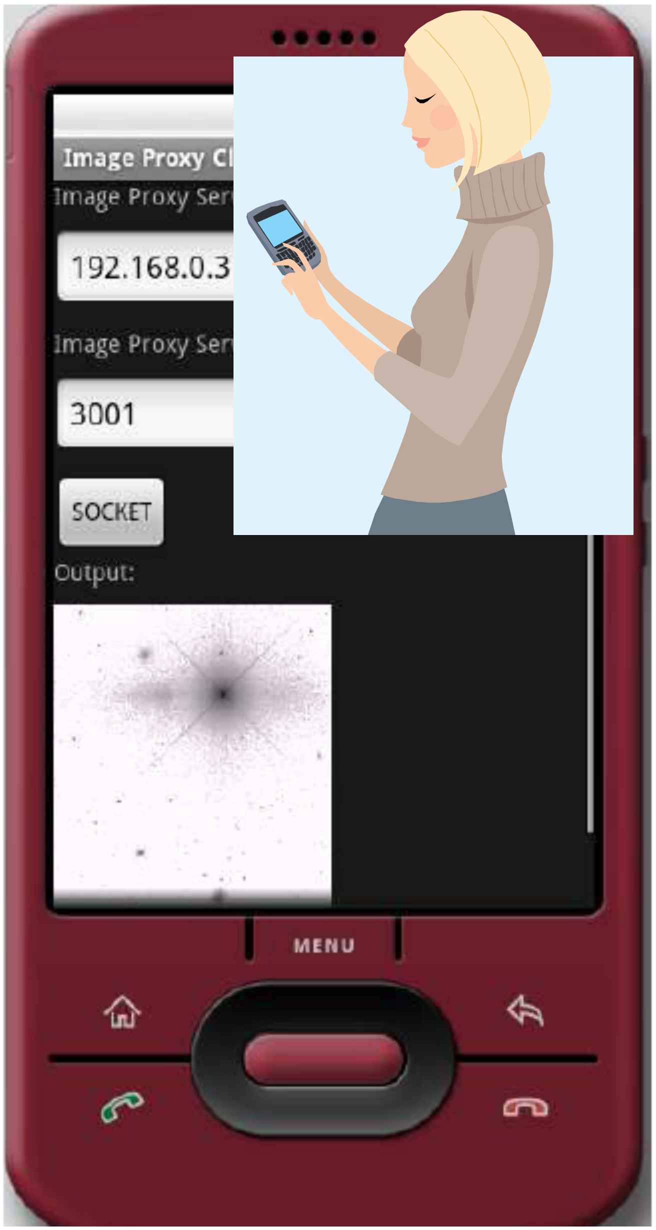


Green proxy accelerates communication 20-75%

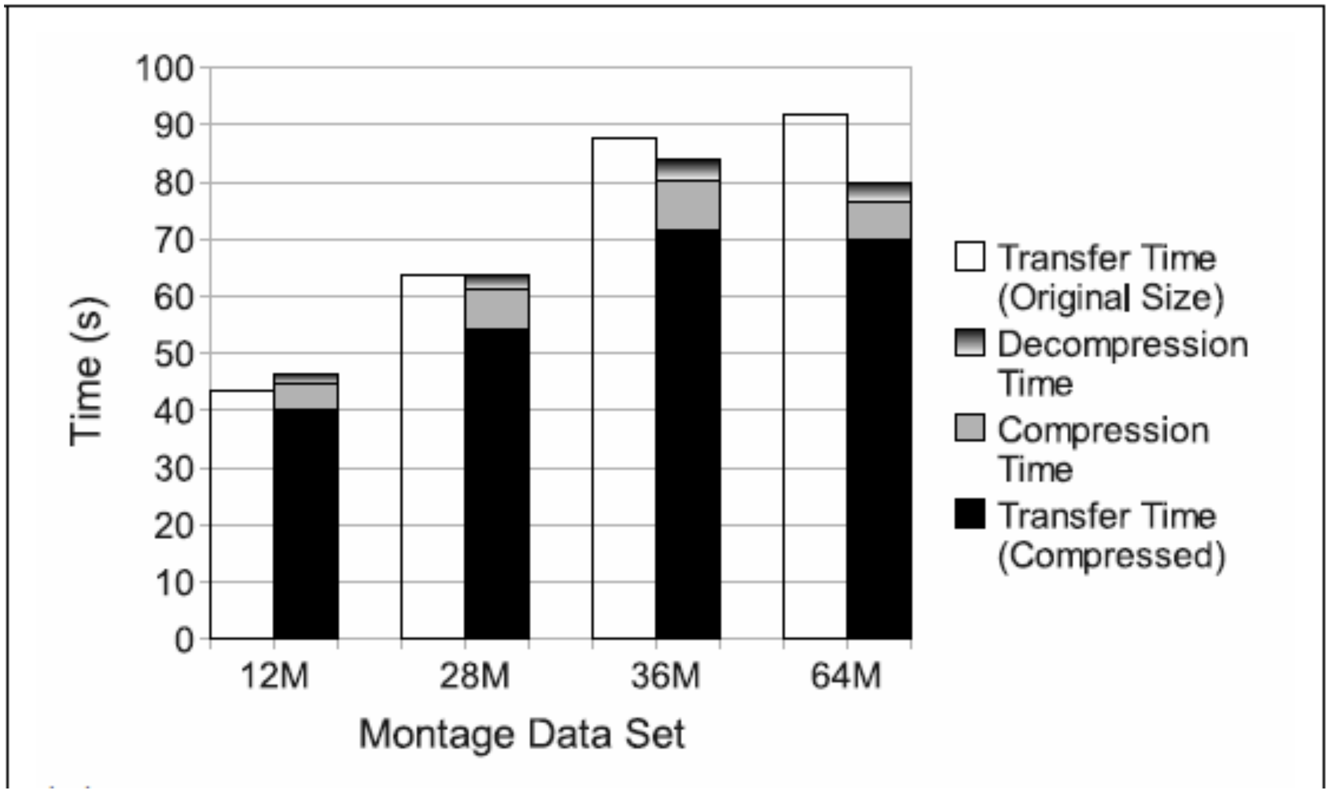
Inside Montage …



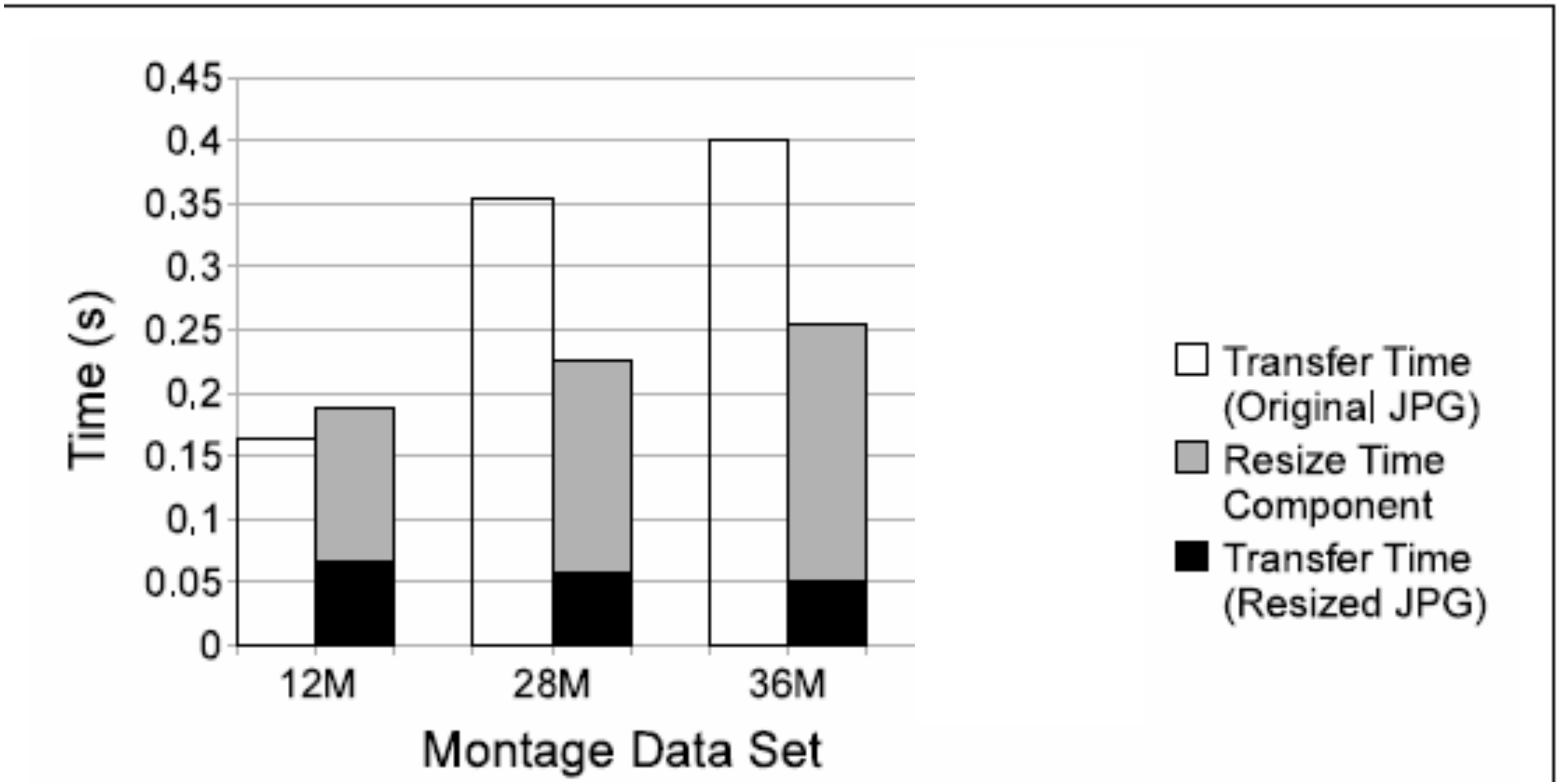
From Montage to the end-user



Desktop User



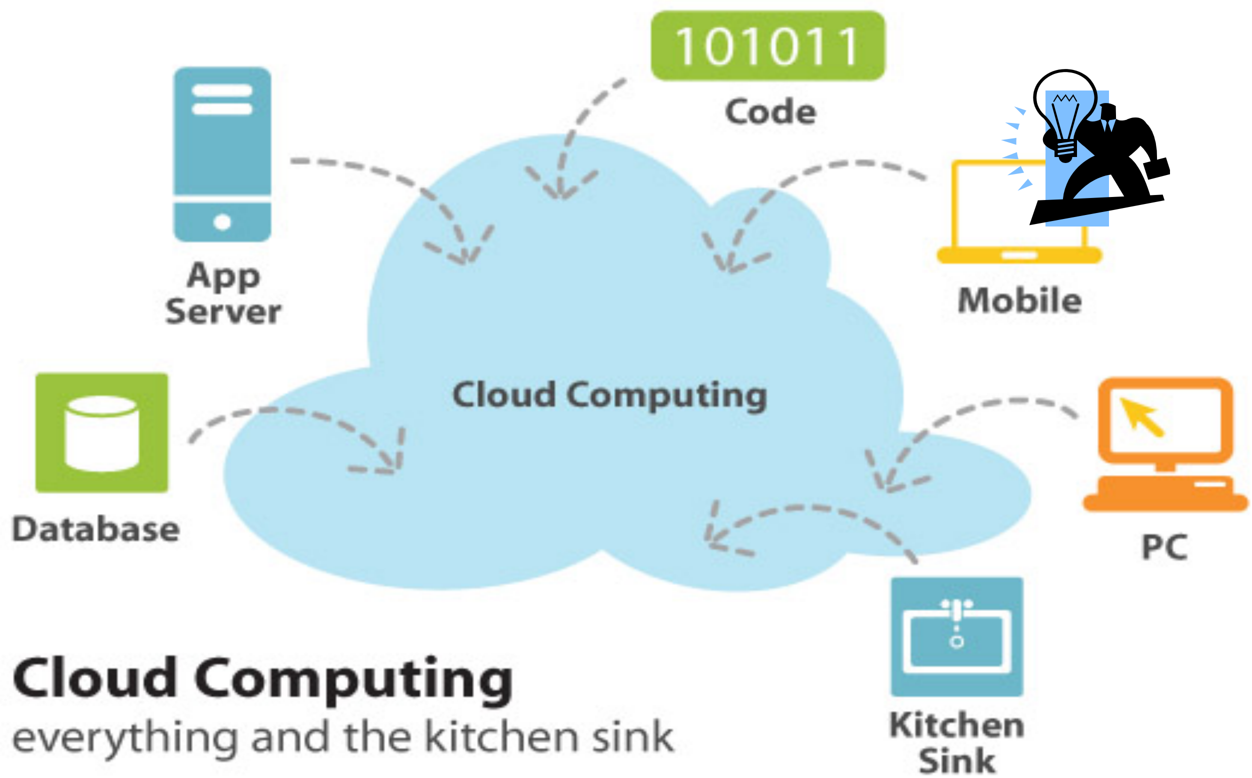
Mobile user



0,45
0.4
0,35
0.3
0.25
0.2
0.15
0,1
0.05
0
Time (s)
12M
28M
36M
Montage Data Set
Transfer Time (Original JPG)
Resize Time Component
Transfer Time (Resized JPG)

Summary

- Conventional clouds attempt to tame a "distributed world"
  - data, computation, people
- Wide-area "awareness" can be key to performance
  - Cloud-cloud, Cloud-user interactions
  - Wide-area MapReduce



Thank you! Questions?