Evaluating Storage Systems for Scientific Data in the Cloud

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Introduction

- Clouds offer ad-hoc clusters with computation, storage and networking resources to carry out distributed application execution
- To effectively utilize these resources, additional setup and systems are required
- Goals of the current work:
  - Characterize IaaS clouds for data oriented applications
  - Evaluation of contemporary storage solutions on clouds
  - Combine Many-Task execution systems with backend storage solution providers to obtain an operational environment for application execution and report on performance

Motivation

- According to a 2013 XSEDE cloud survey report, a majority of users have difficulty in managing data in clouds. About 27% of the users use the Amazon S3 storage system for their data needs.
- A quote from a 2011 report on Magellan experience:

  Tools [are needed] to simplify using cloud environments ... and enhancements to Map Reduce models to better fit scientific data and workflows [are needed] for scientific applications.

- Big Data and increasingly I/O intensive workflows
- Different application requirements: read, write, read-after-write
- Availability: In clouds, node-local storage is available during the life of a VM instance and can be effectively utilized

Overview

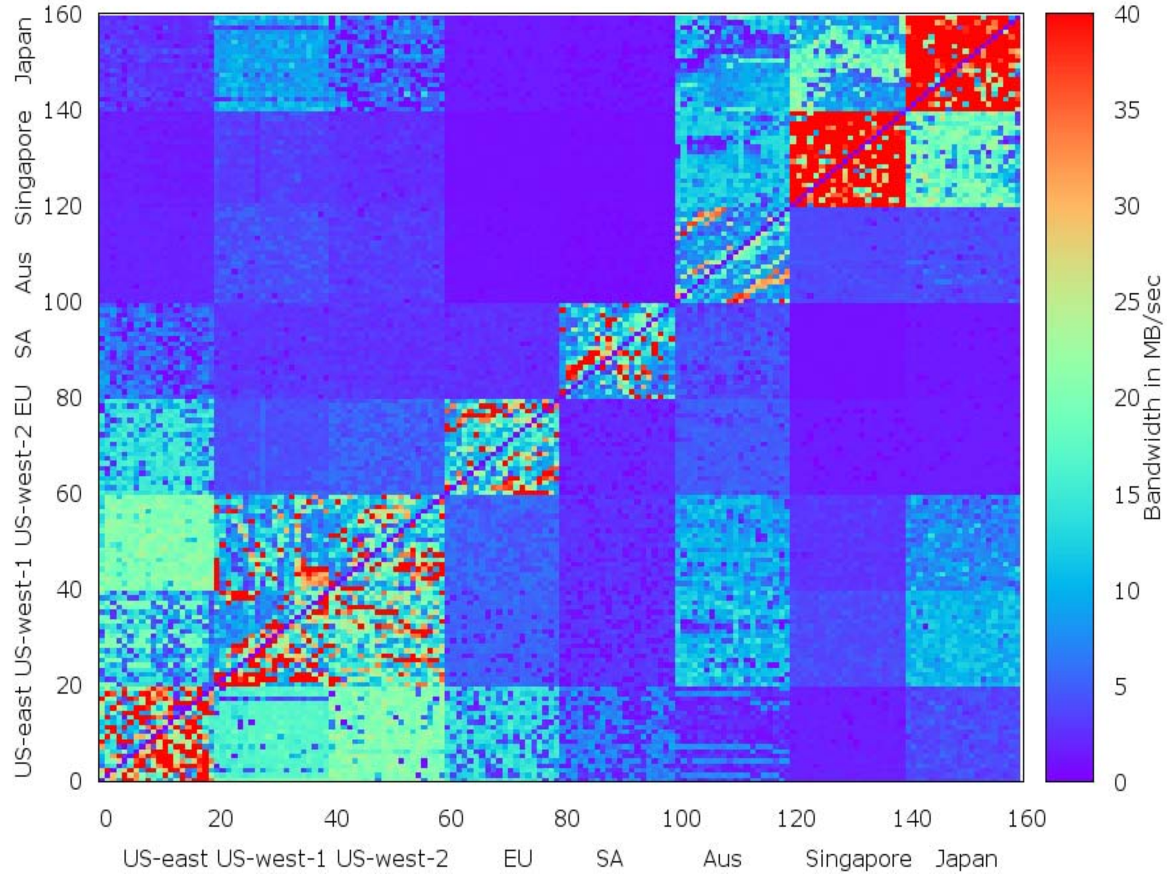
- Introduction
- Motivation
- The Nature of the cloud
  - Network characteristics between cloud regions
- Storage systems
  - MosaStore, Chirp/Parrot
  - Amazon S3, HDFS
- Swift
- Experiments
  - Raw Performance
  - Real-World Applications
  - Application Results
- Summary

The Nature of the Cloud

- Physically, cloud systems comprise of geographically distributed resources.
- Unlike traditional clusters, these resources are non-uniformly distributed with irregular connectivity
- Crucial to understand the network connectivity for data oriented distributed applications in the clouds
- We perform two experiments on Amazon AWS cloud:
  - Measure bandwidths between instances of each of the eight global regions
  - Measure latencies between instances of each of the eight global regions
- We chose a representative 20 instances from each region resulting in a 160X160 matrix

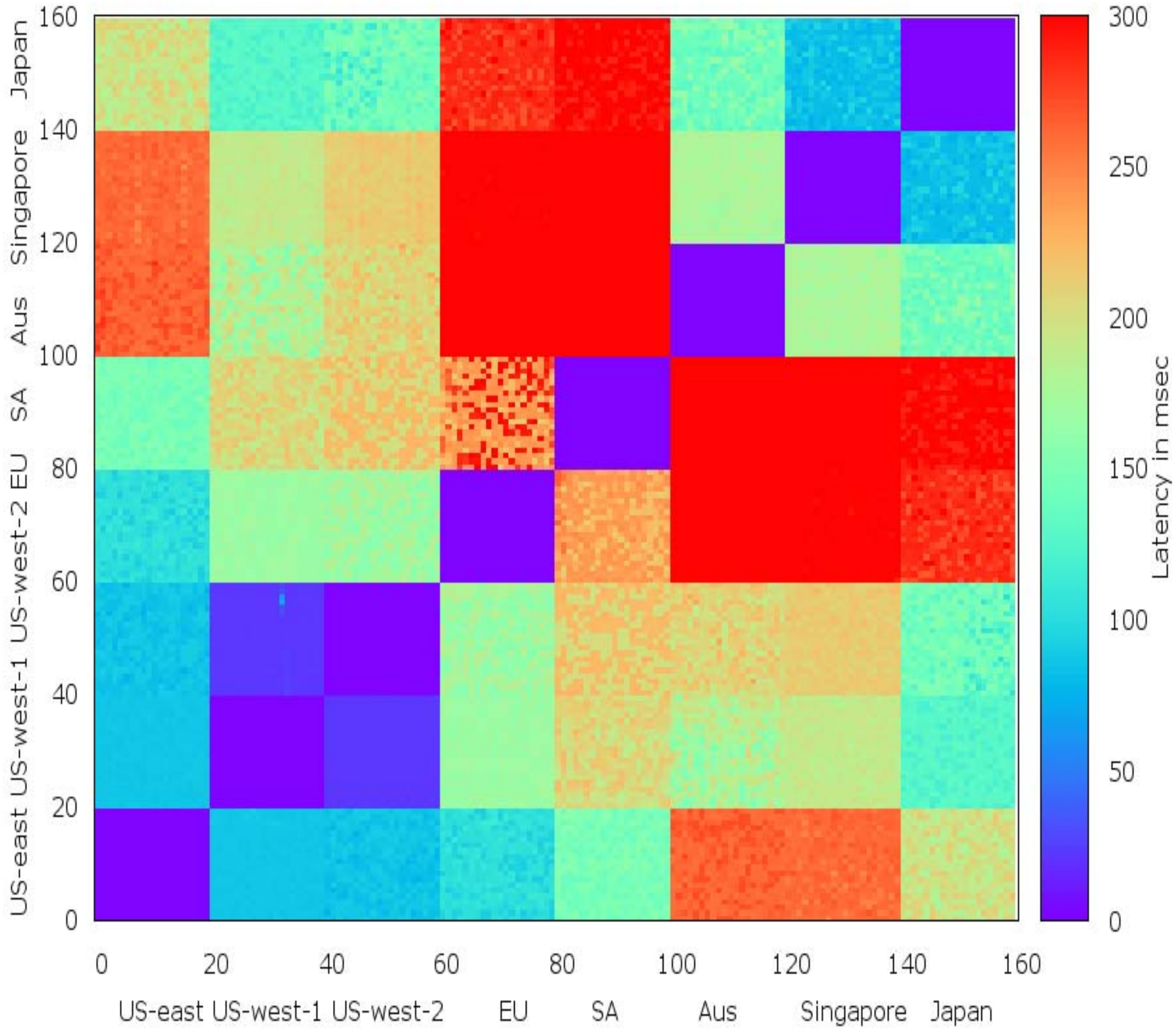
Cloud Regions Bandwidths: Some Observations

- North American regions well-connected
- EU well-connected to US-east
- Aus well-connected to US-west and Japan, Singapore
- Japan and Singapore well-connected among themselves but poorly connected with rest of the world



Cloud Connectivity: Latencies

- Similar pattern as bandwidths (lower the better)
- More symmetrical and islands
- Fast connections between US regions
- Fast connections between Aus-Singapore-Japan



Conclusions from Cloud Network Analysis

- Want to answer: How much data can we move in cloud and how fast?
- Resources from global cloud must be chosen carefully to improve performance versus cost
- For instance, a cluster of 1000 nodes between Japan and Singapore might be faster than the one between US-east and US-west
- Isolated regions such as South America and EU with one datacenter each may not be combined with other regions for distributed computing
- Smart storage strategies are very relevant in this scenario: exploit locality, replication, caching
- Carefully chosen storage servers can benefit cloud executions

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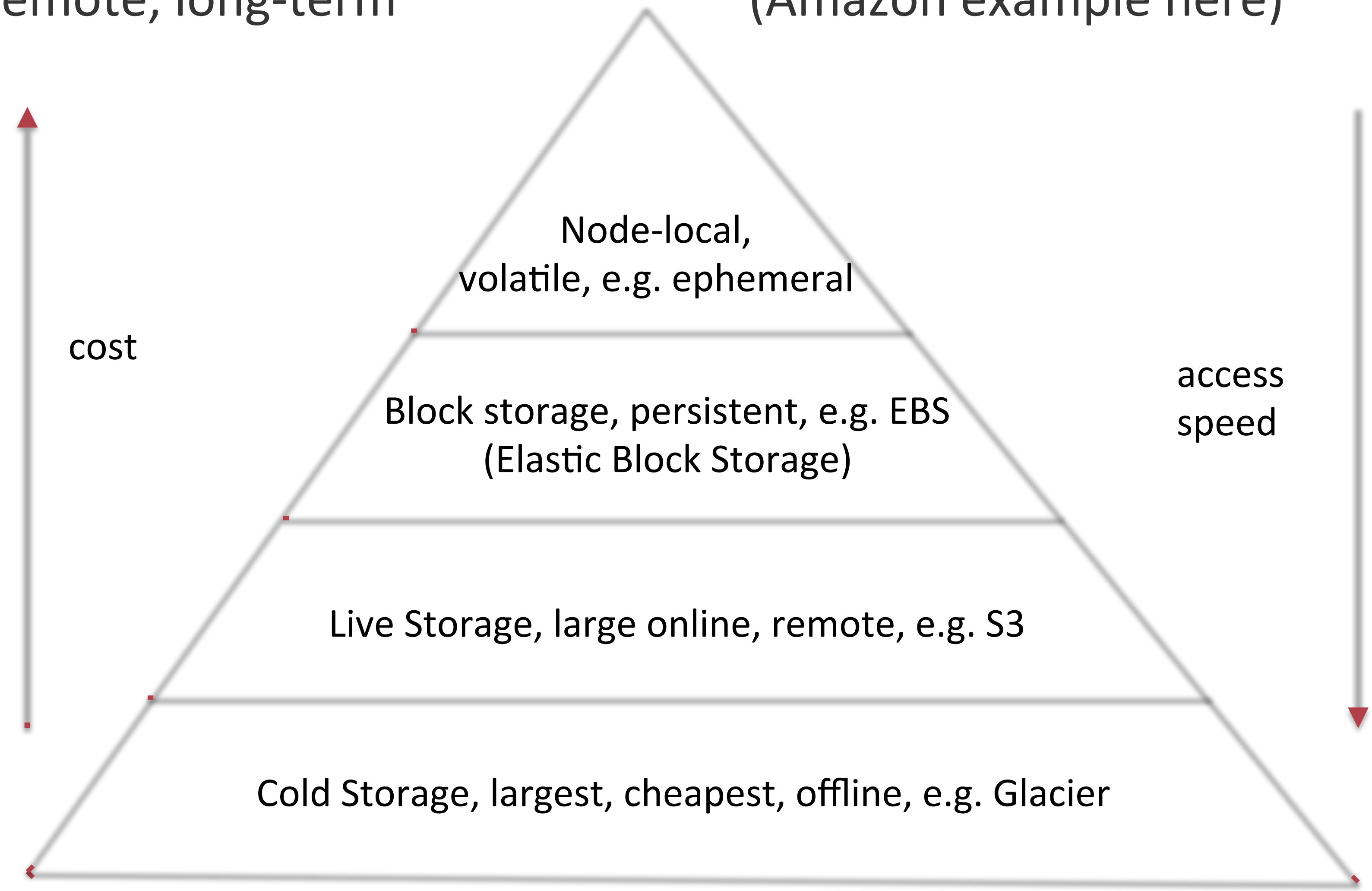
Storage Systems

- Clouds offer different storage solutions: node-local, extended, remote, long-term (Amazon example here)



Storage Systems

- Clouds offer different storage solutions: node-local, extended, remote, long-term

- Modern performance oriented storage systems
- Widely used in modern cloud applications: e.g., Google Drive
- Why are they important?
  - Gives unified view of distributed physical systems
  - Fast, synchronous, consistent
  - Enables implicit data movement across shared-nothing nodes
- Example systems: Distributed File systems, Key-Value stores
- Here we evaluate:
  - Research storage systems: Mosastore, Chirp/Parrot
  - Commercial storage systems: Hadoop HDFS, Amazon S3

Research Storage Systems: Chirp and MosaStore

Chirp

- A user-level storage system that provides a virtualized, unified view of data over multiple real file systems (e.g., over file systems deployed over independent clusters)
- Parrot is an interceptor layer that traps an application's POSIX file system calls and redirects them to Chirp
- A combination of Parrot and Chirp can thus provide a POSIX-accessible storage environment

MosaStore

- A low-overhead, user-level distributed storage system based on FUSE
- Optimize data distribution under-the-hood via striping and replication
- Can expose the details of data location for workflow level optimization

Commercial Storage Systems: Amazon S3 and Hadoop HDFS

Amazon S3

- A remote object storage system provided by Amazon
- Access via a get/put API or FUSE-enabled mount
- Preconfigured and ready-to-use but a paid service

Hadoop HDFS

- A High-throughput filesystem designed to store data on share-nothing cluster of machines
- Well-suited to node-local computational models such as MapReduce but can be used with workflow models via external APIs

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Swift

- A parallel scripting framework with many-task dataflow execution system
- Swift composed workflows drives the execution and data movements concurrently in conjunction with application logic thus stressing the underlying storage systems
- Two implementations
  - Classic Swift/K (Karajan), mostly HTC oriented, single task store (submit host), uses explicit data movement on non-storage enabled, non-shared filesystems, has some optimizations for collective data movement
  - New Swift/T (Turbine), more HPC focused, distributed task store, much faster task dispatching rates, requires shared storage systems (either physical, e.g. HPC, or via software, e.g. w/ Mosa on clouds)

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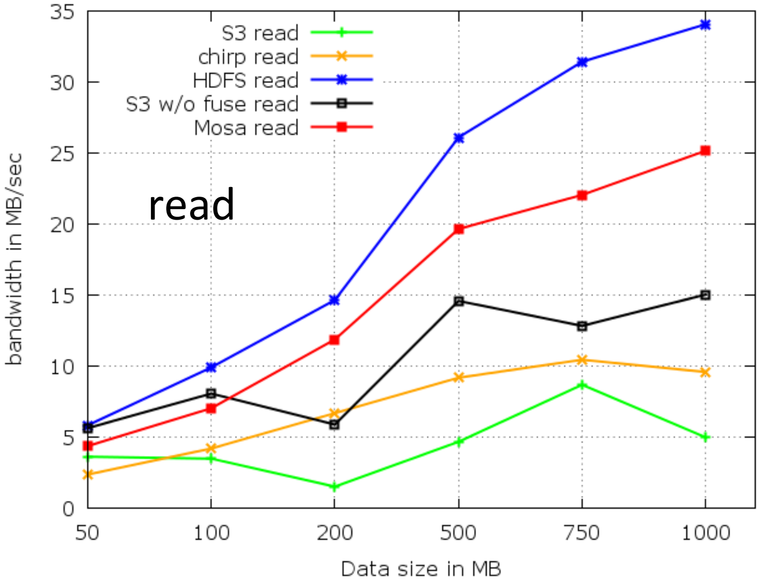
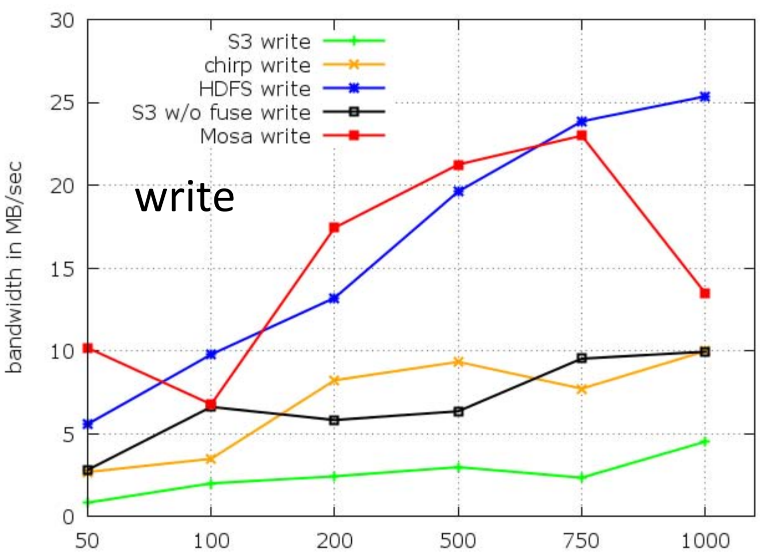
Experiments

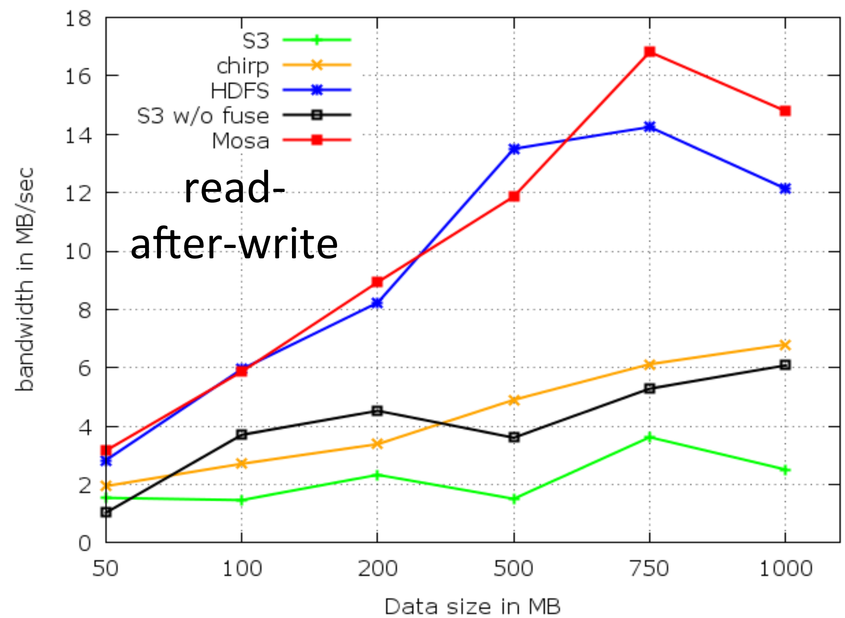
- Workflow-driven raw I/O performance benchmarks:
  - Concurrent reads from storage system to local file system
  - Concurrent writes to storage systems from cloud nodes
  - Read-after-Write
- Used 40 “m1.large” (2-cores, 8G memory) Amazon instances spread between two regions: US-east and US-west
- Measure bandwidths for data sizes: Between 50 and 1000 MB
- Mosa, Chirp and HDFS use node-local storage to aggregate space
- S3 use remote S3 object store via FUSE-mounted S3FS and remote get-put operations on named S3 bucket

Raw performance benchmarks



- HDFS and MosaStore leads the performance
- In the crucial read-after-write benchmarks, both MosaStore and HDFS performs closely with MosaStore outperforming HDFS for large data sizes
- Amazon S3 remote storage significantly slower than MosaStore and HDFS
- We chose MosaStore for further application execution

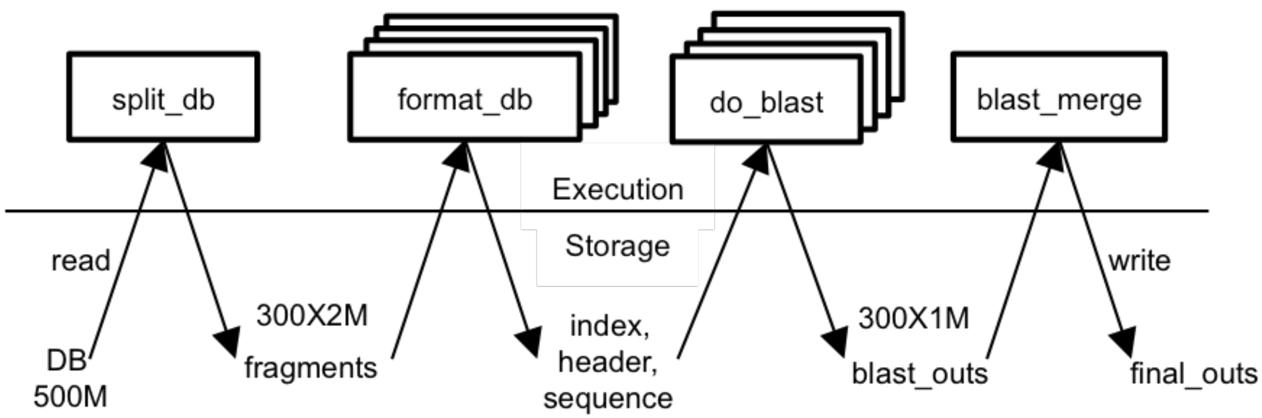




Maheshwari et. al., swift-lang.org

Real-World Applications (1) : Parallel BLAST

- A protein alignment search tool, BLAST performs searches from a given protein database.
- *Parallel* BLAST splits the protein database into fragments and runs many instances of BLAST simultaneously over the split database.
- The results from each of the fragment search are merged to give the final result.



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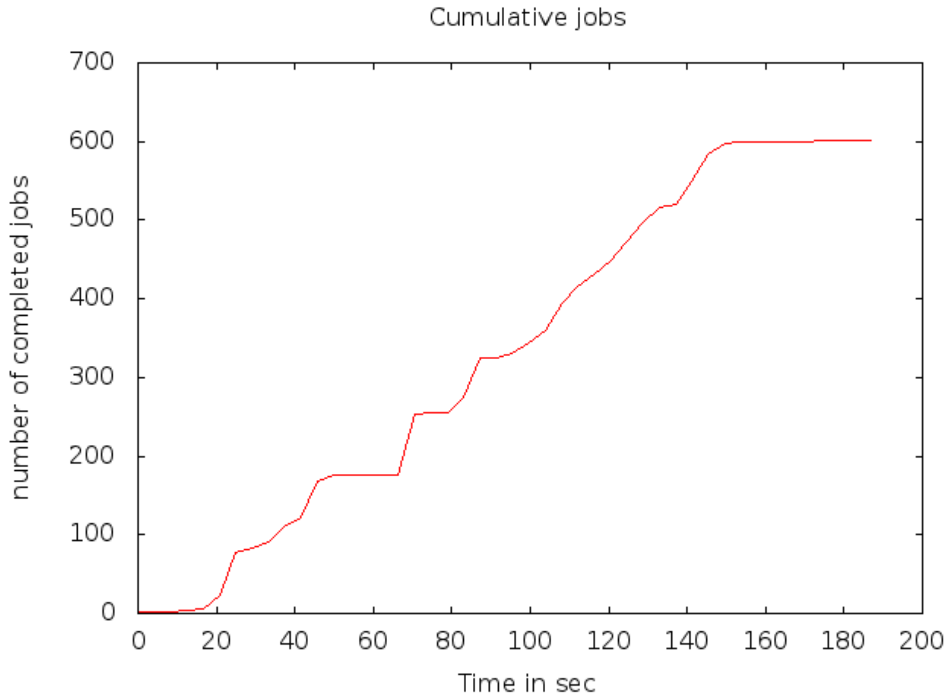
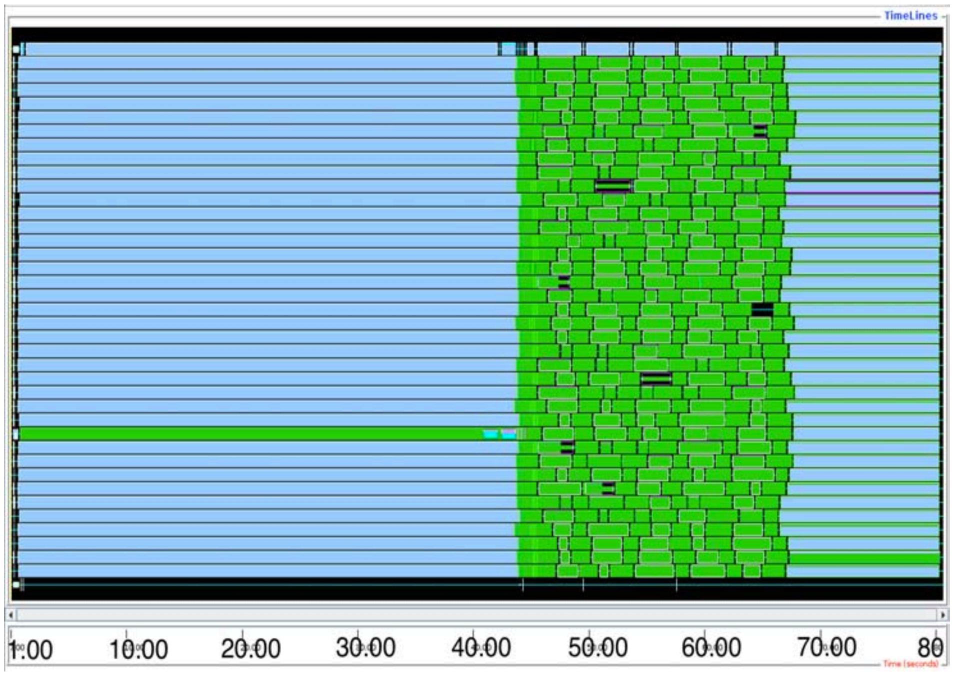
Application results: Swift running Parallel BLAST on Amazon with MosaStore





Explicit data movement between cloud instances with Swift/K

Implicit data movement by Mosastore using Swift/T
44% faster than explicit movement

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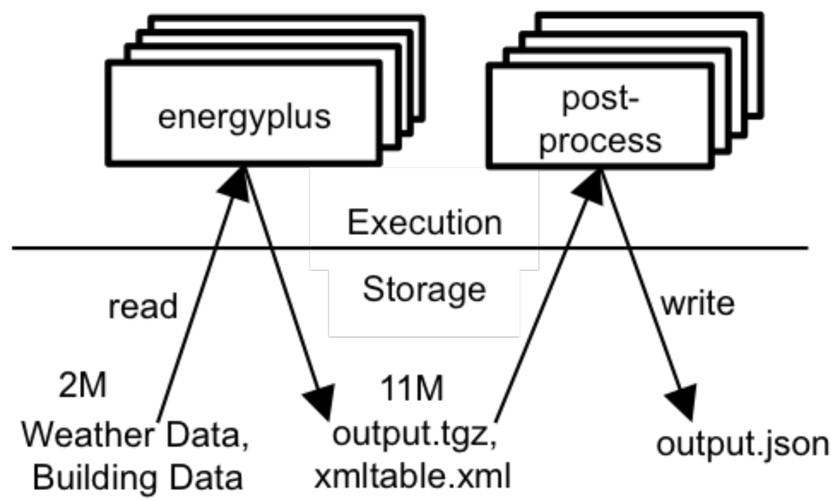
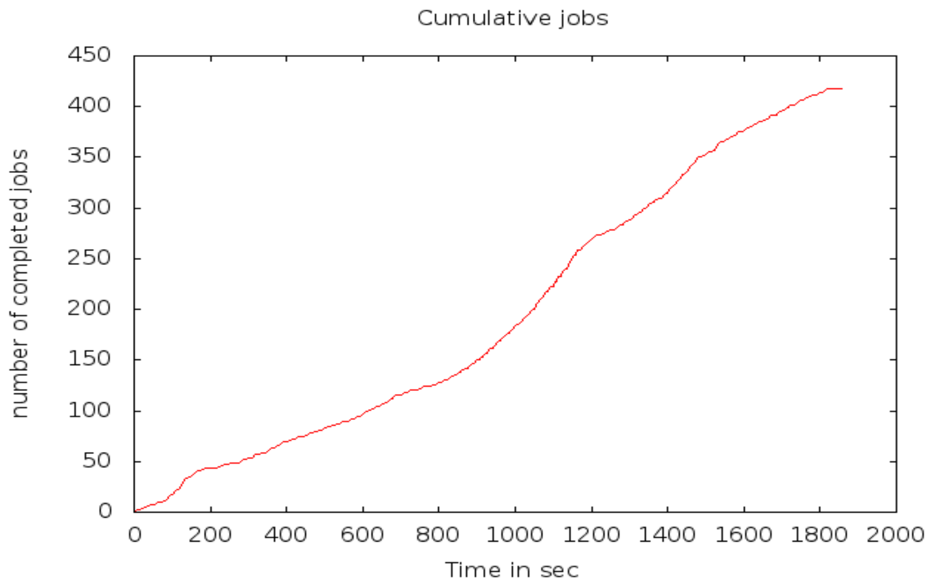
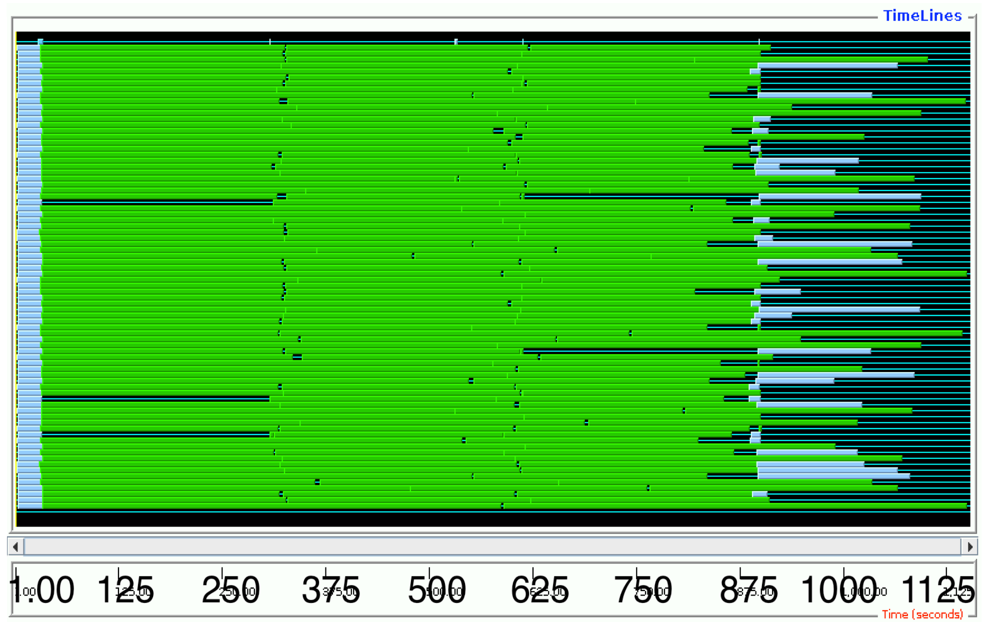
Real-World Applications (2) : EnergyPlus

- A suite of energy analysis and thermal load simulation programs for buildings.
- Takes an ensemble of climate, historical and structural parameters as input and projects the future energy requirements
- Two steps: run ensemble and do results formatting as post-process.



Application results: Swift running EnergyPlus on Amazon with MosaStore





Explicit data movement between cloud instances with Swift/K

Implicit data movement by Mosastore using Swift/T
59% faster than explicit data movement

Summary

- Globally implemented clouds rely heavily on Internet backbone, resulting in non-uniform and variable network characteristics, which application deployments must take into account
- Applications with medium immediate storage requirements can run effectively by aggregating the cloud node-local space with the help of storage solutions; these solutions almost always perform better that the dedicated object store provided by clouds such as Amazon S3
- Swift has been shown to perform better on clouds with implicit files systems (e.g. MosaStore), but can fall back to explicit data movement if needed

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