Scibox: Online Sharing of Scientific Data via the Cloud

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Matthew Wolf[†,‡], Stephane Ethier[‡], Scott Klasky[‡]

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Outline

- Background and Motivation
- Problems and Challenges
- Design and Implementation
- Evaluation
- Conclusion and Future Work

Cloud Storage is Popular

Easy-of-use

Pay-as-you-go model

Universal accessibility

Good scalability and durability

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Works based on cloud storage

- Dropbox, GoogleDrive, iCloud, SkyDrive, and etc.

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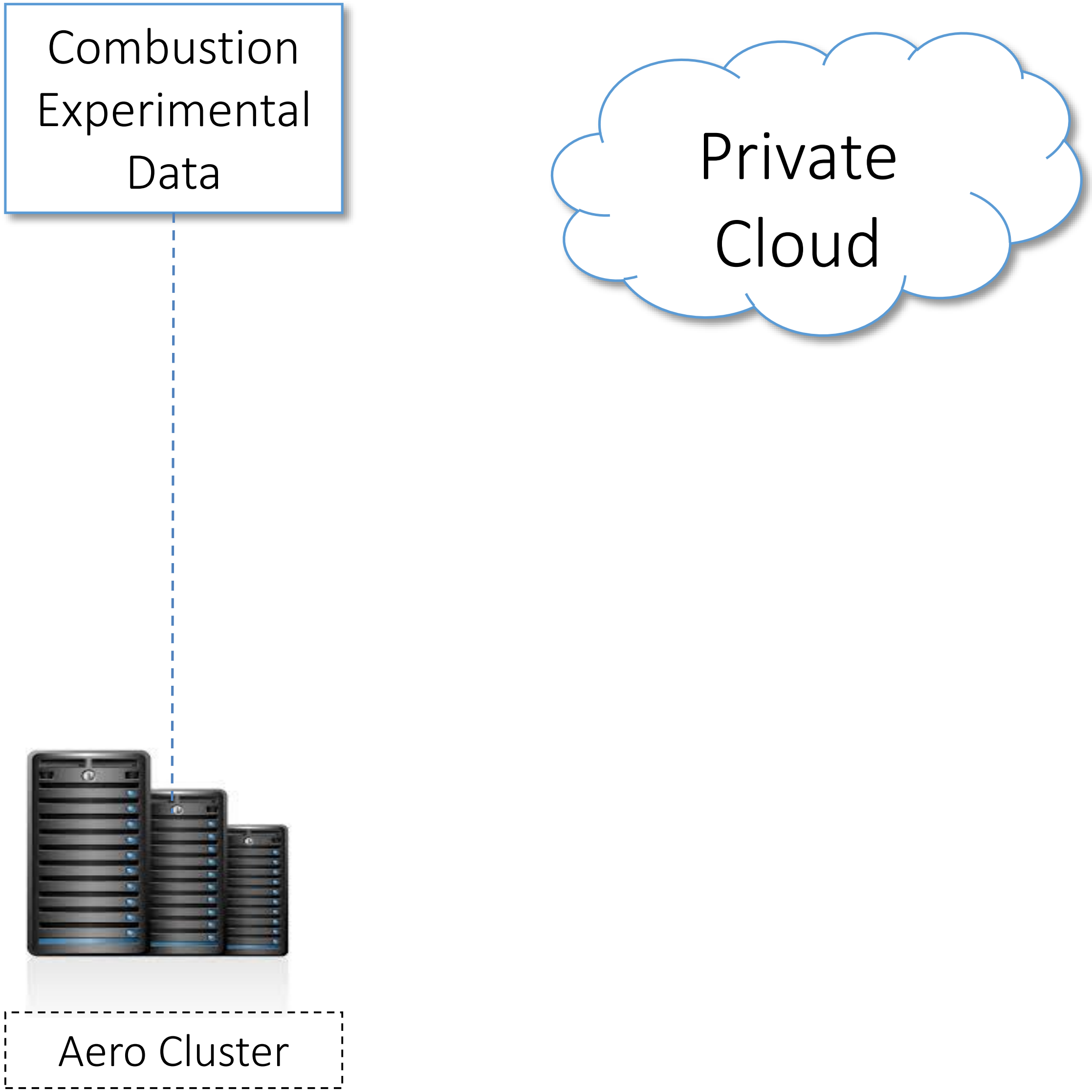
→ Scibox: focus on scientific data sharing

Use Cases for Cloud Storage

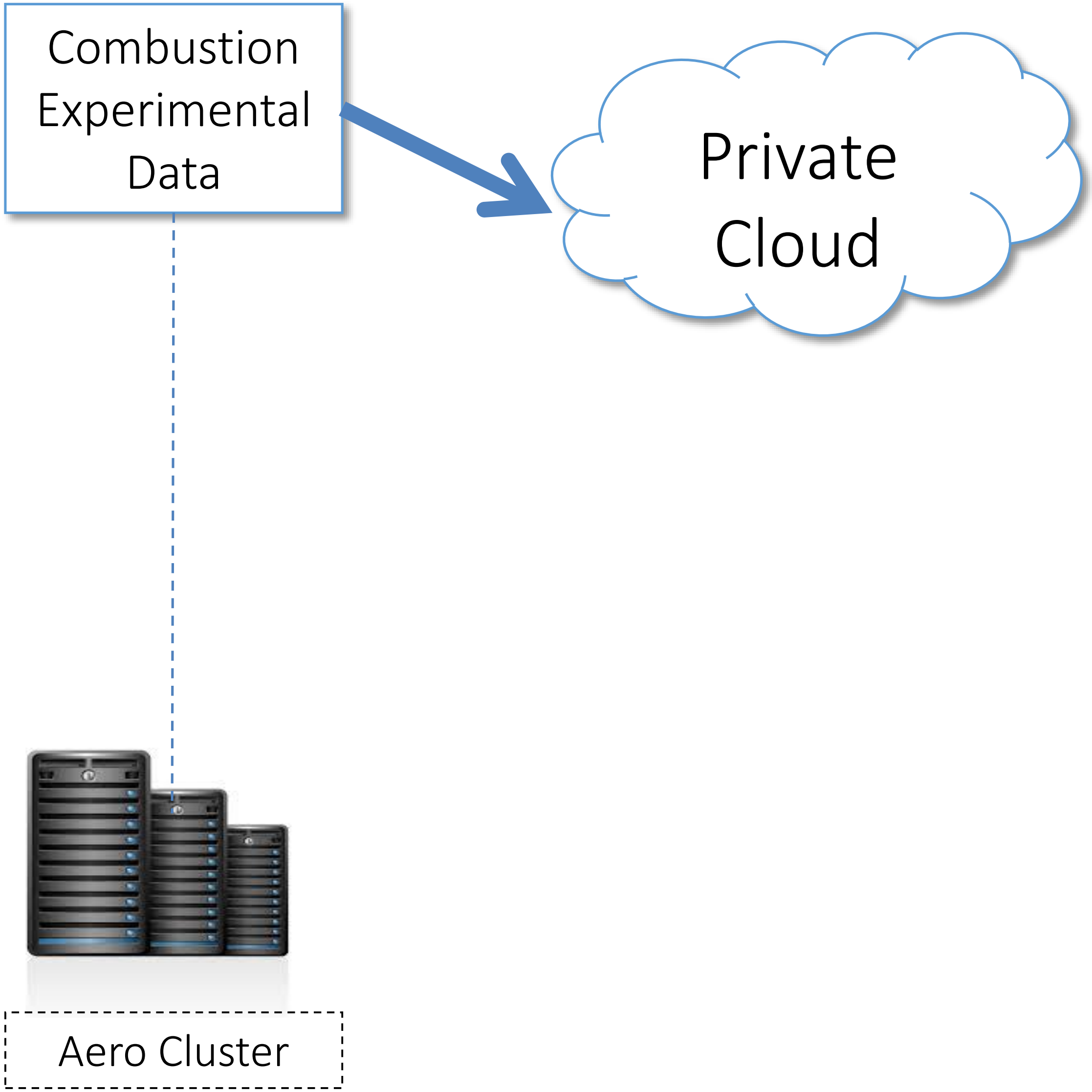


Combustion Experimental Data

Private Cloud

Aero Cluster

Use Cases for Cloud Storage



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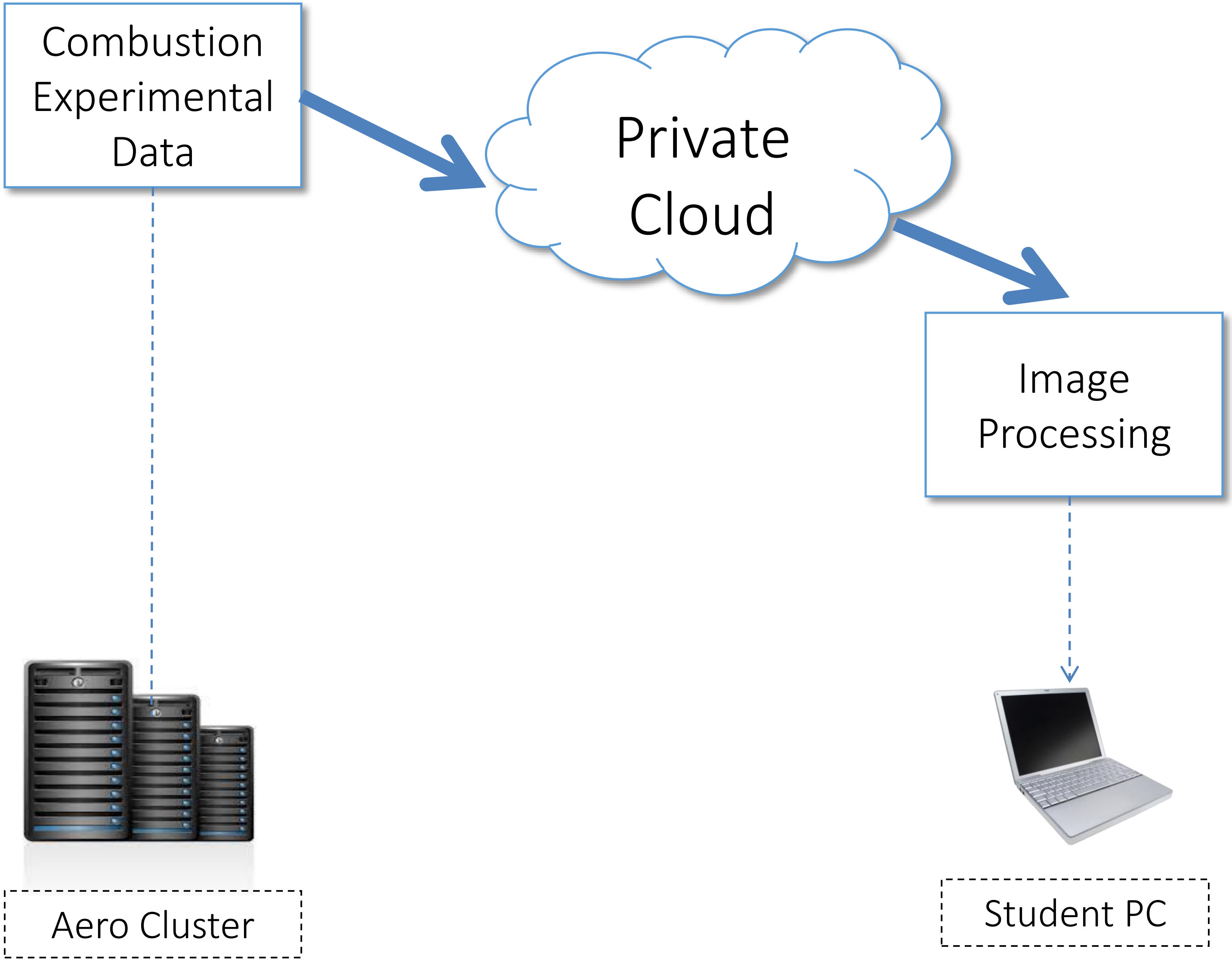

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Image Processing

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Student PC

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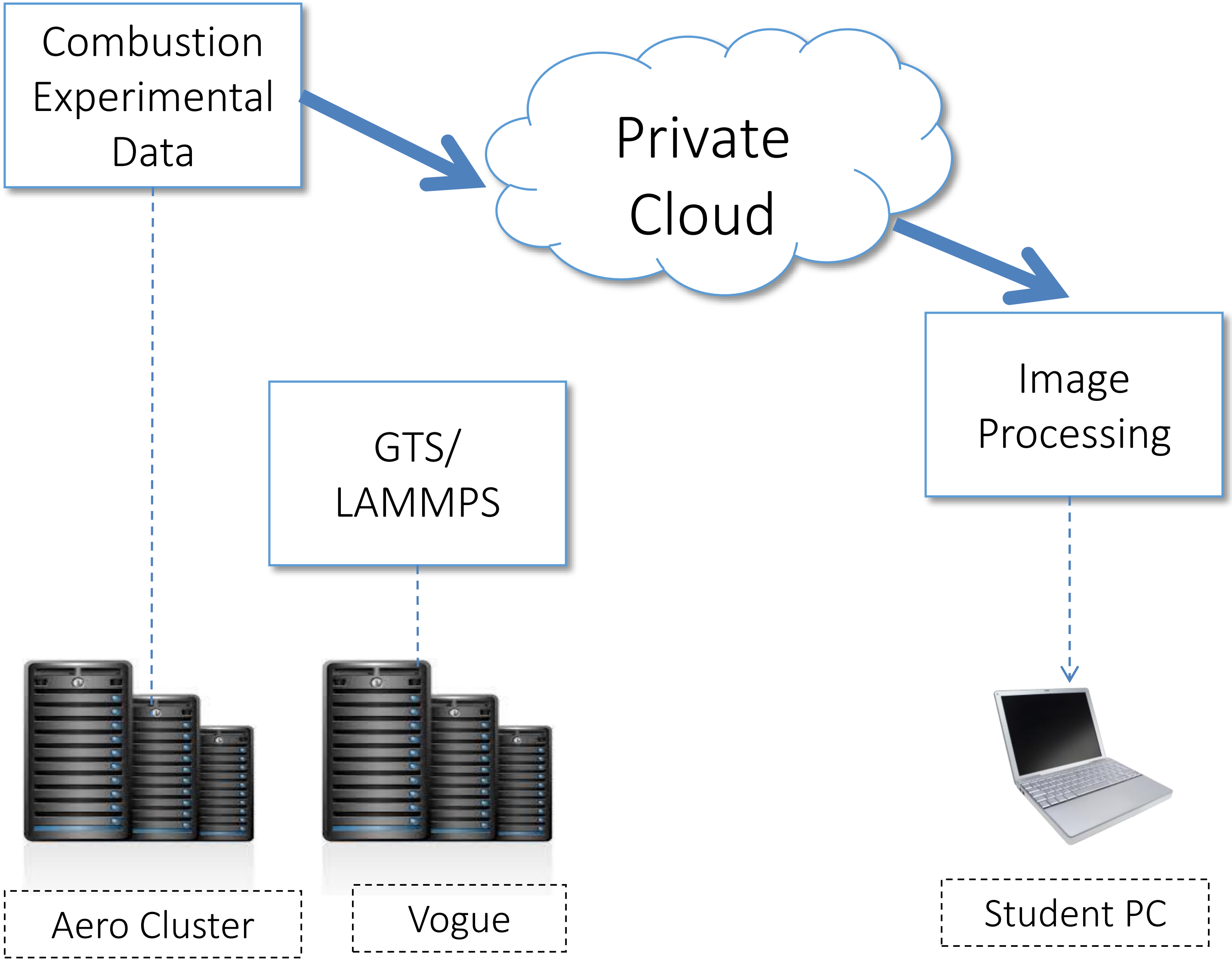

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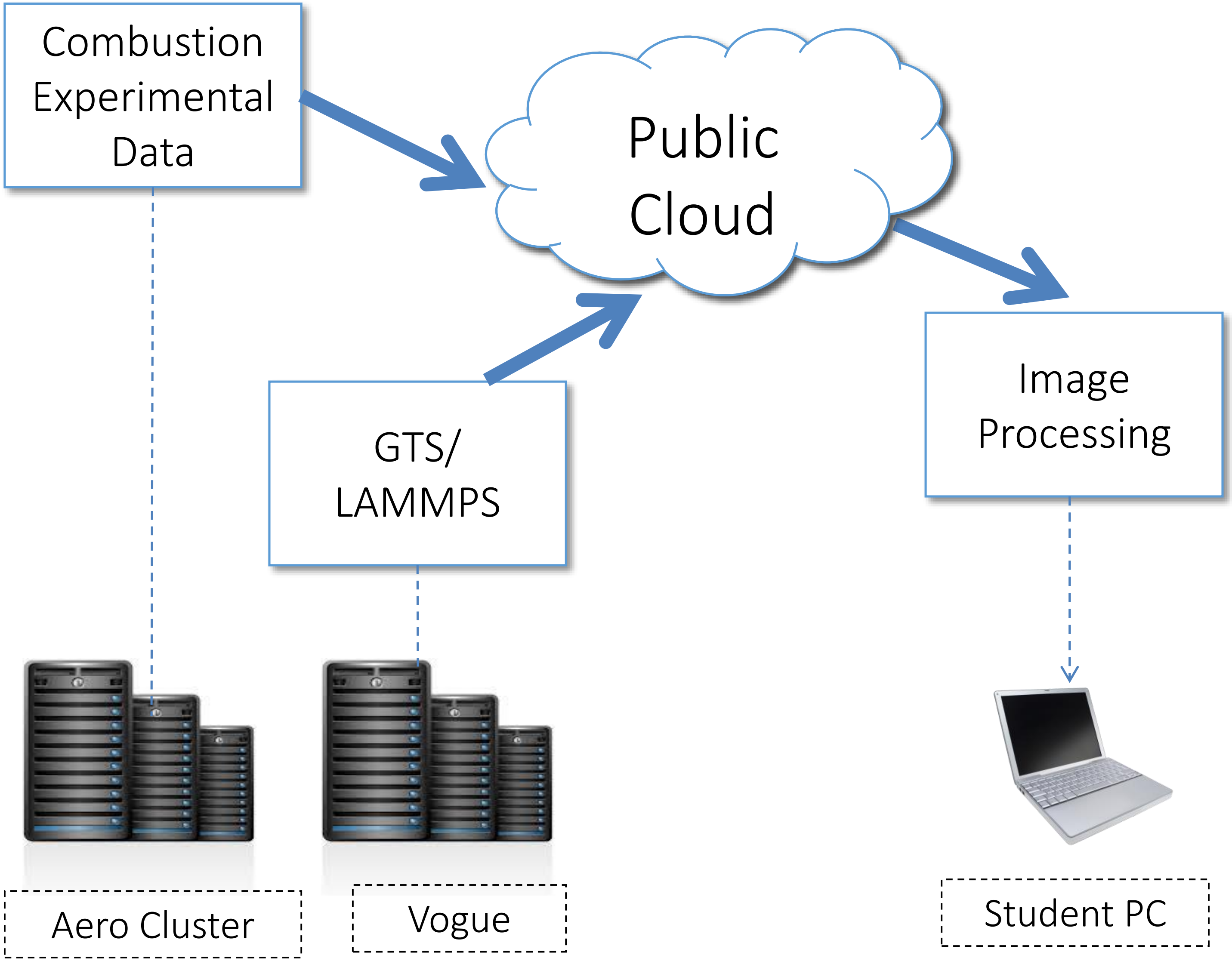

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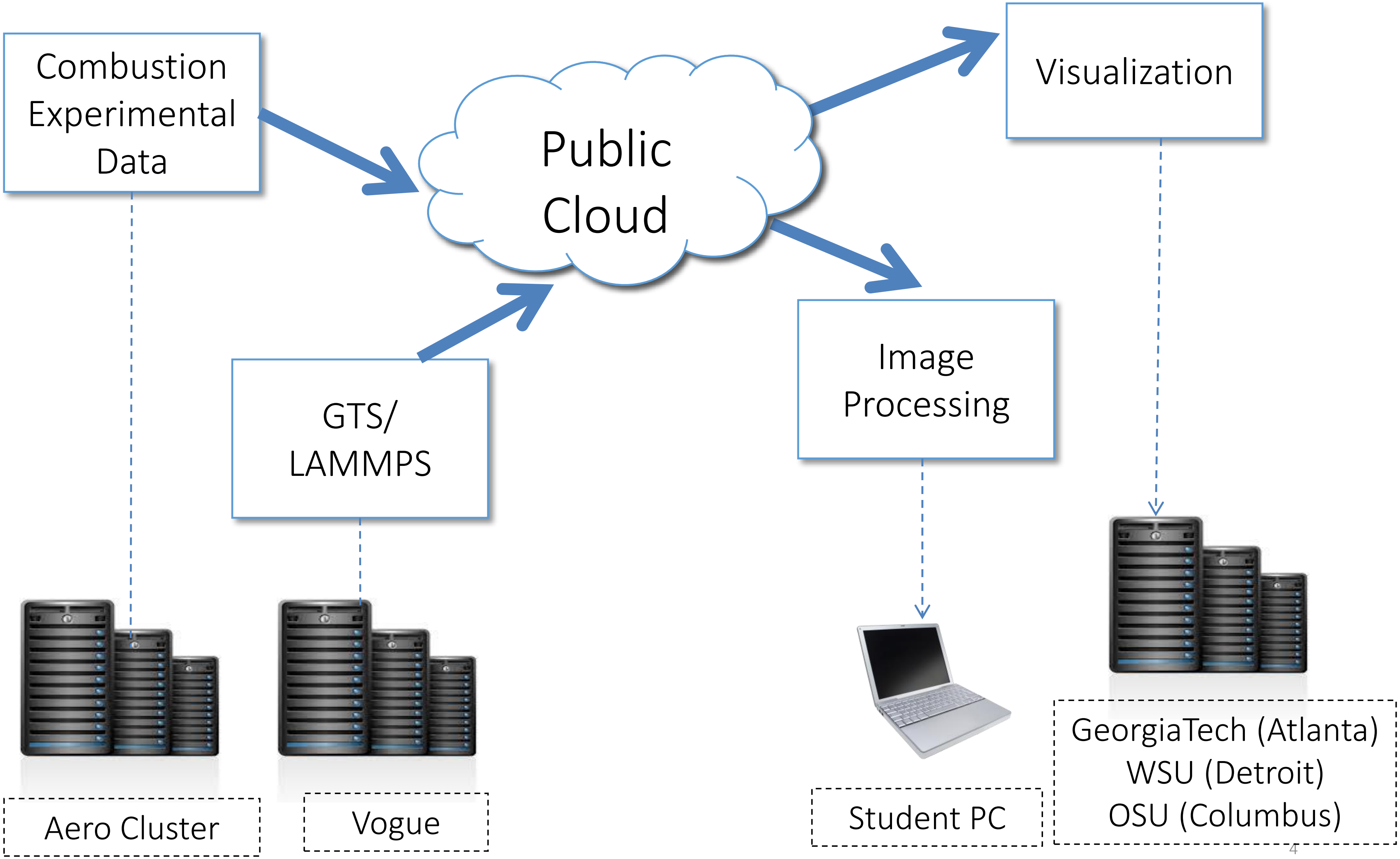

Combustion Experimental Data

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Visualization

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Vogue

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GeorgiaTech (Atlanta)
WSU (Detroit)
OSU (Columbus)

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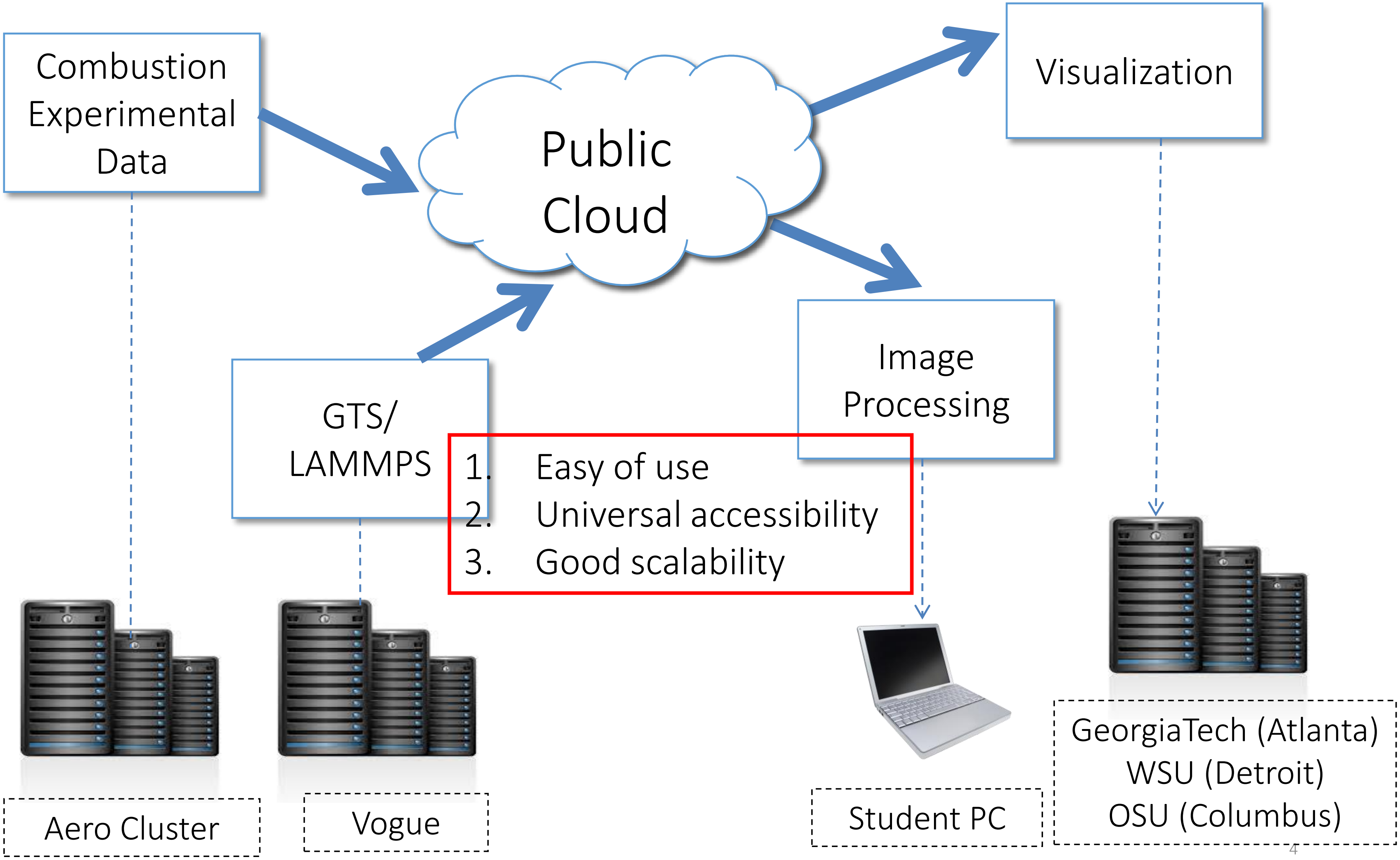

1. Easy of use
2. Universal accessibility
3. Good scalability

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Scientific applications are data-intensive

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An example:

A GTS runs on 29K cores on the Jaguar machine at OLCF generates over 54 Terabytes of data in a 24 hour period.

Amazon S3: ~$0.03/GB for storage and $0.09/GB for data transfer out.

Cost: $6635.52/day, increases with increasing number of collaborators

Problem: Too Much Data Movement

Issue: naïve approach transfers lots of data, even if only some of it is needed

Time step 0

A_0 A_1 A_2 … A_n

B_0 B_1 B_2 … B_n

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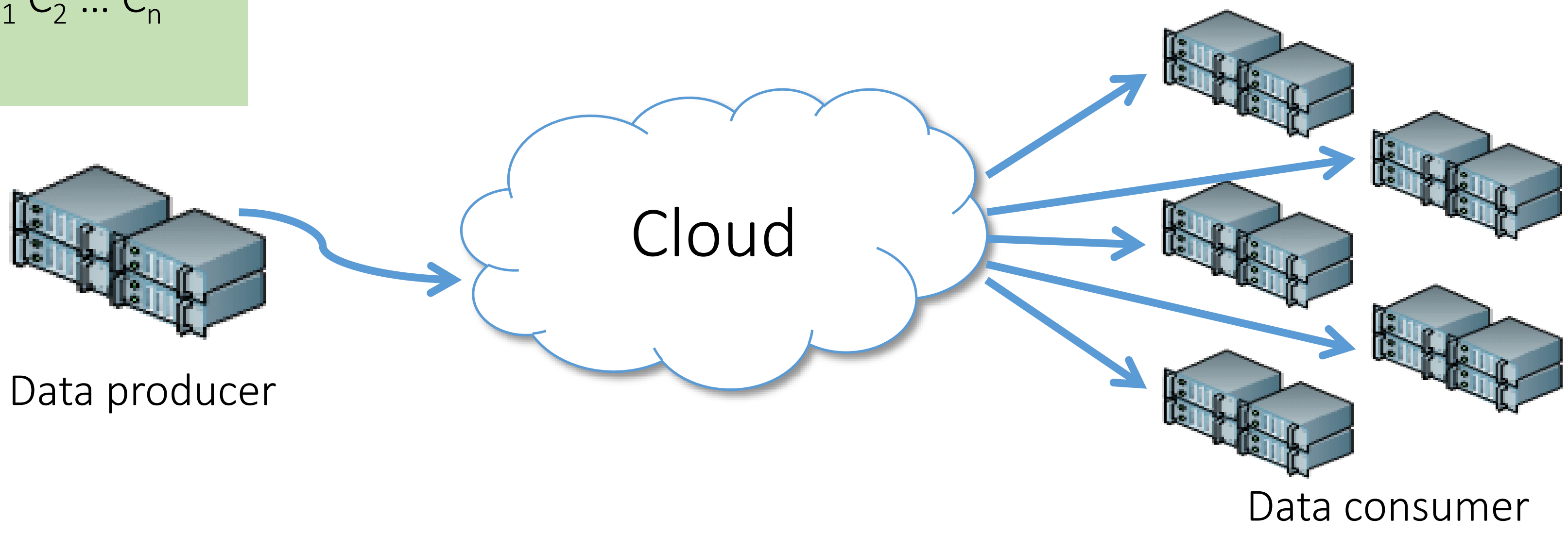
Example

Output of GTS fusion modeling simulation:

Checkpoint data, diagnosis data, visualization data and etc.

Each data subset includes many elements



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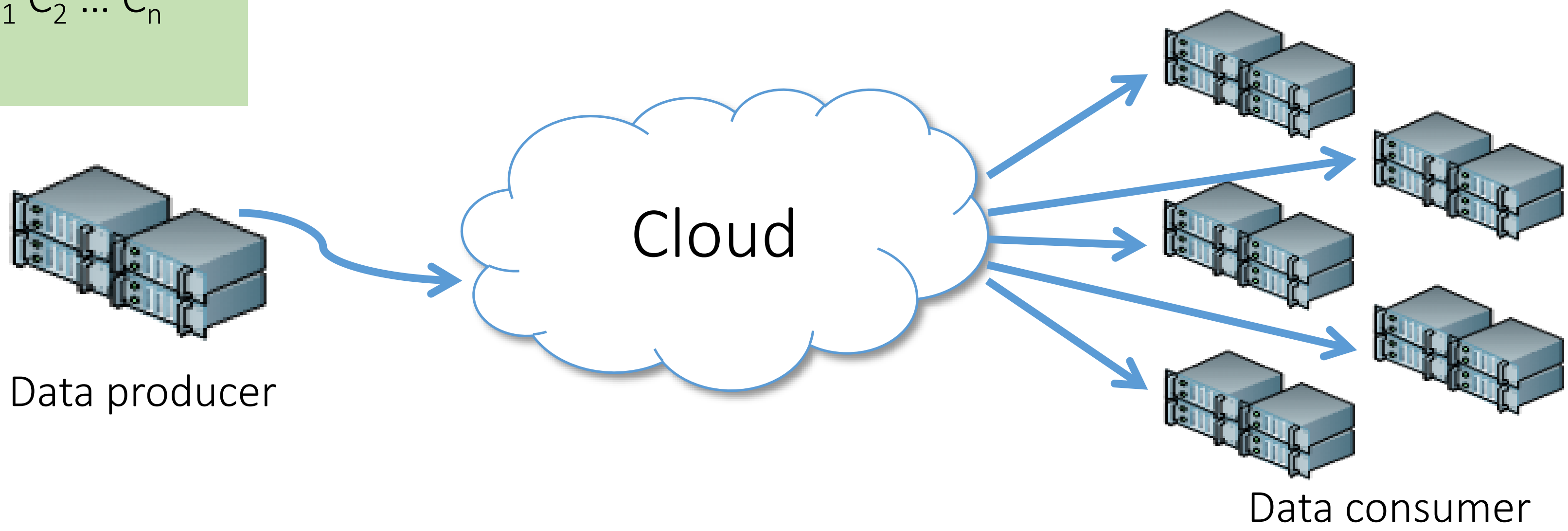

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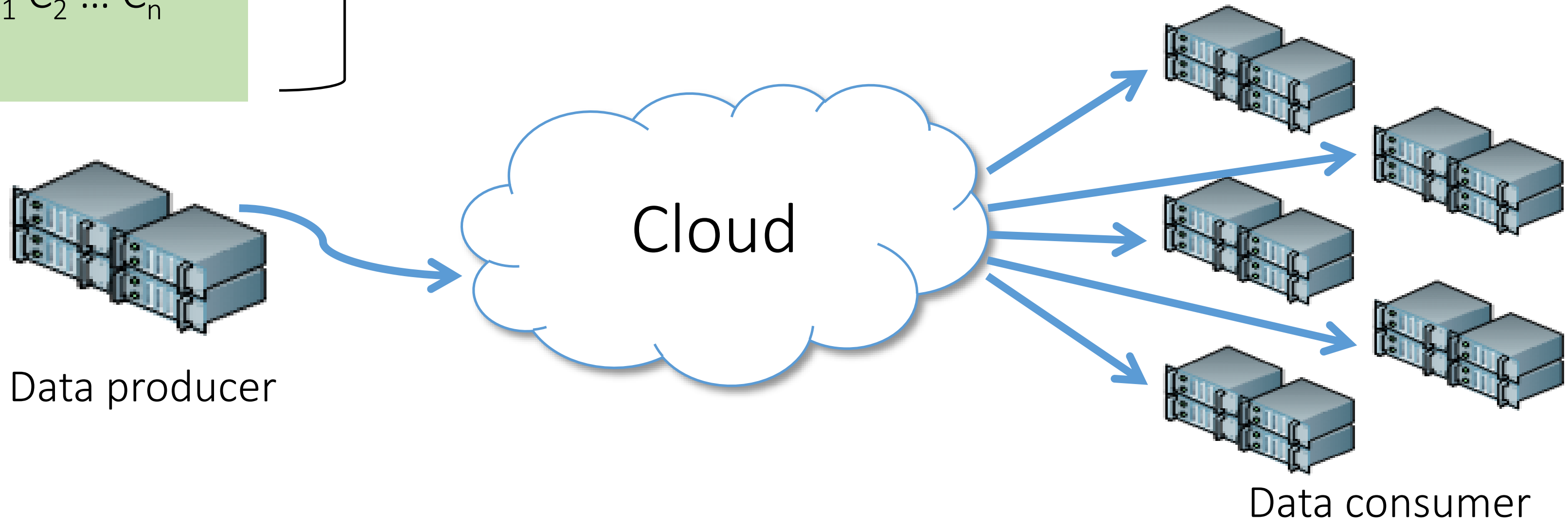
- Scientific data formats: BP/HDF5

  Structured and meta-data rich
- Standard I/O interface: ADIOS

  Almost transparent to users



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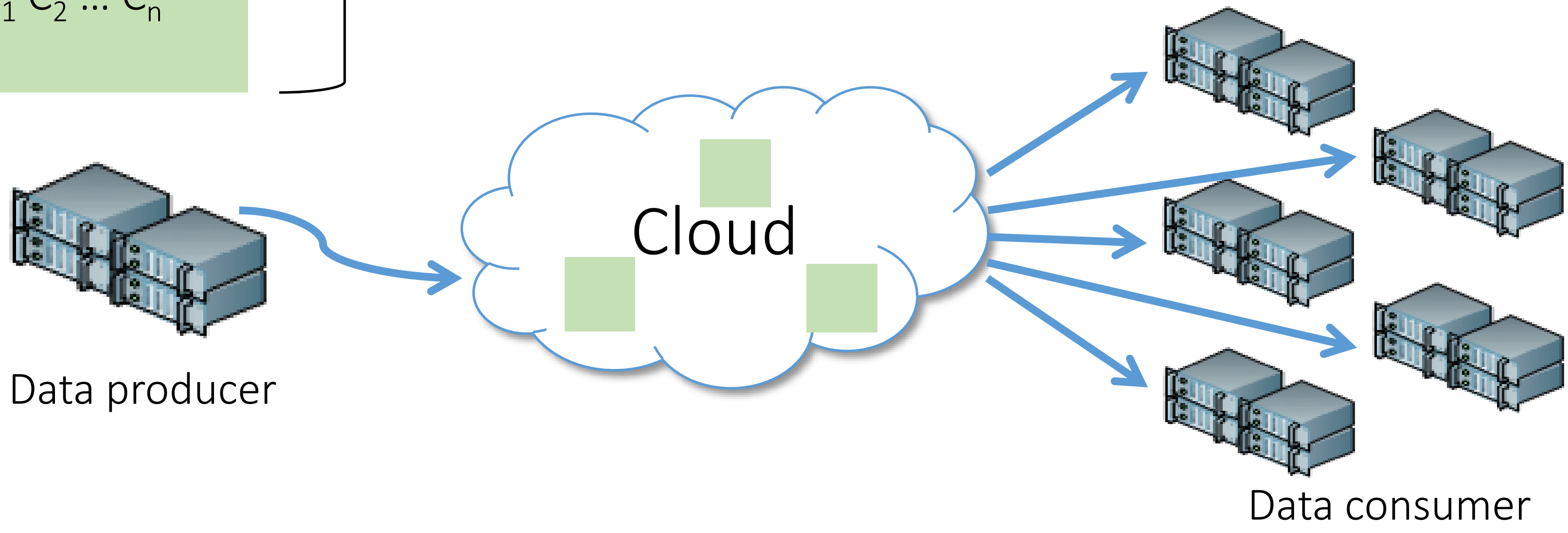

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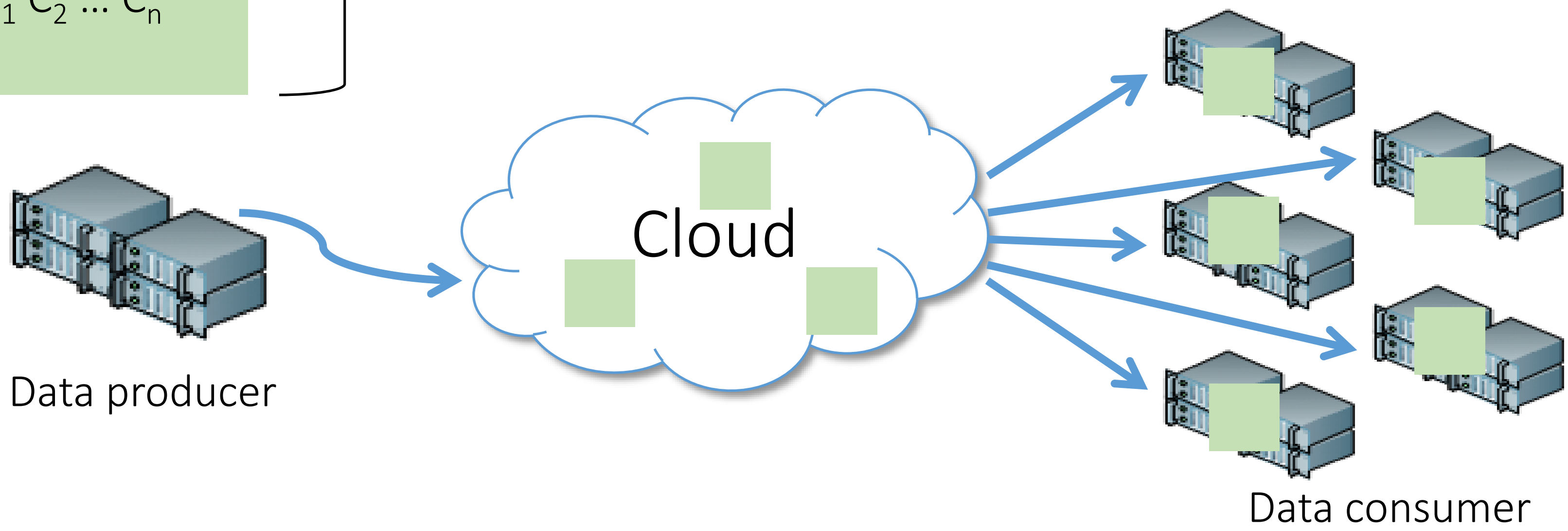

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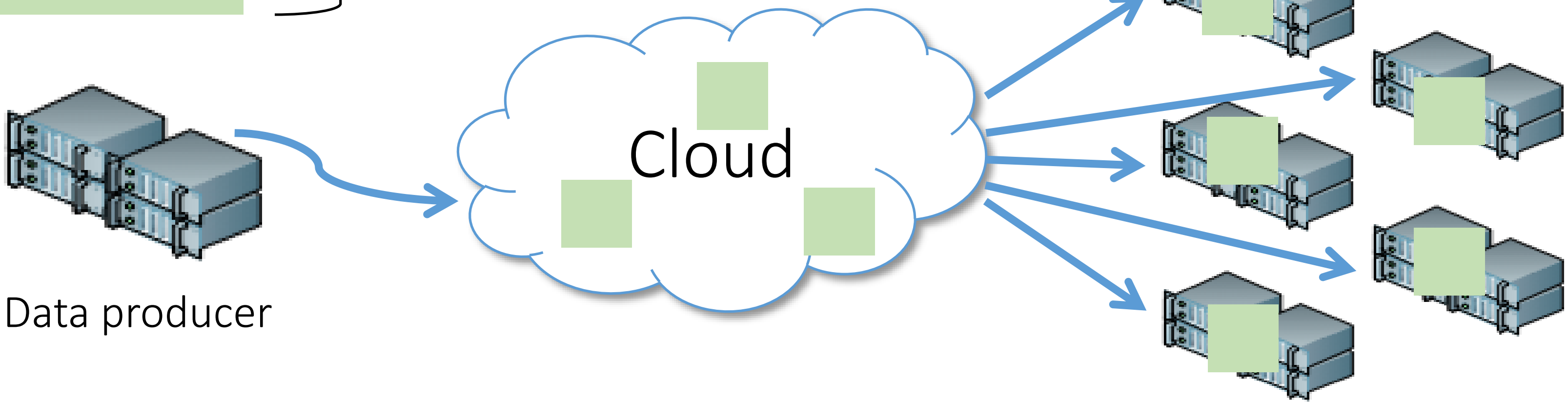

Data consumer

Goal: Reduce data transfer from producers to consumers

Solutions for Minimizing Data Transfers for Data Sharing

Compression

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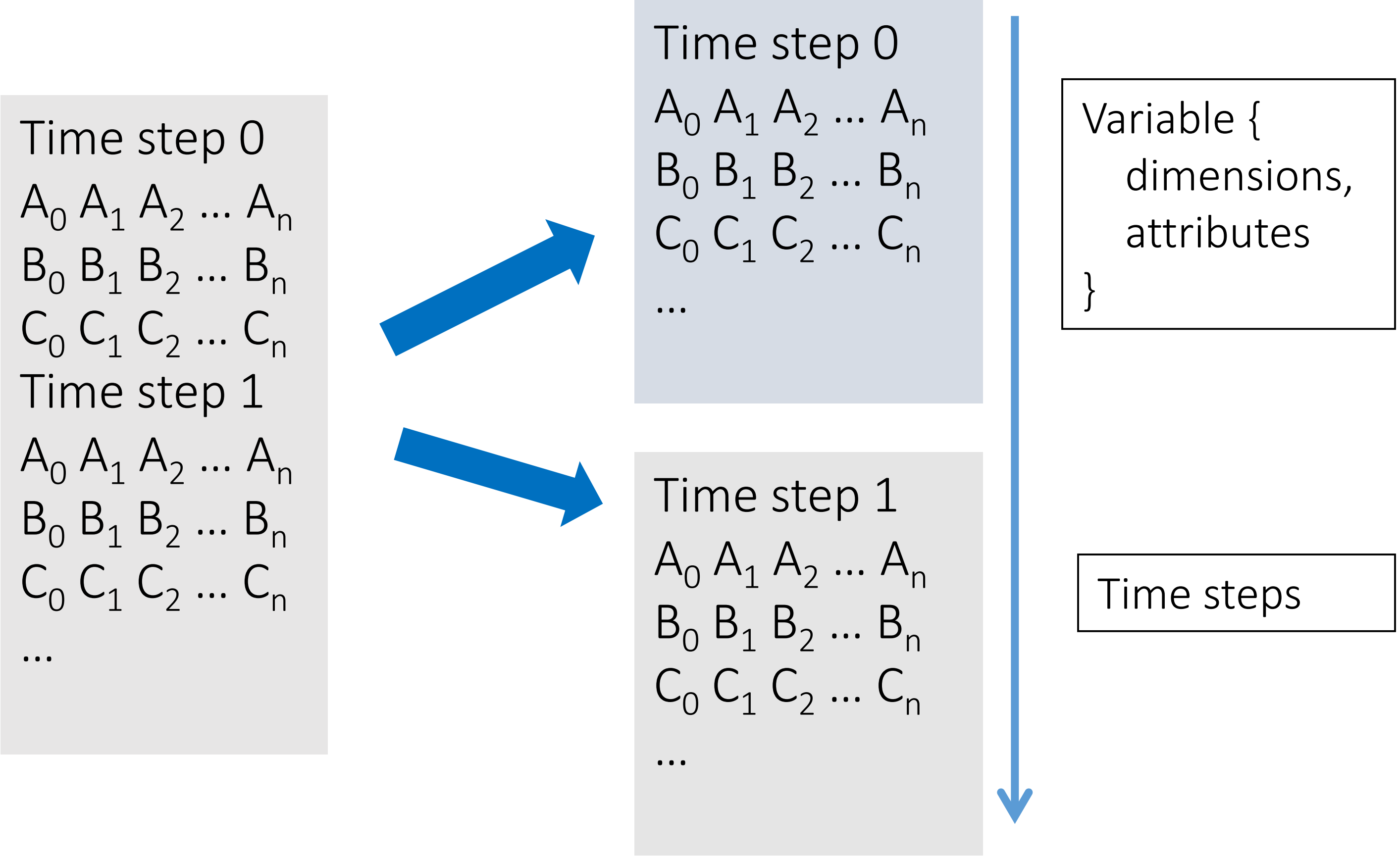
- Minimize data sharing cost in cloud storage via new software protocol (downloads)

Challenge: How to Filter Data

Recall: scientific data is structured and meta-data rich



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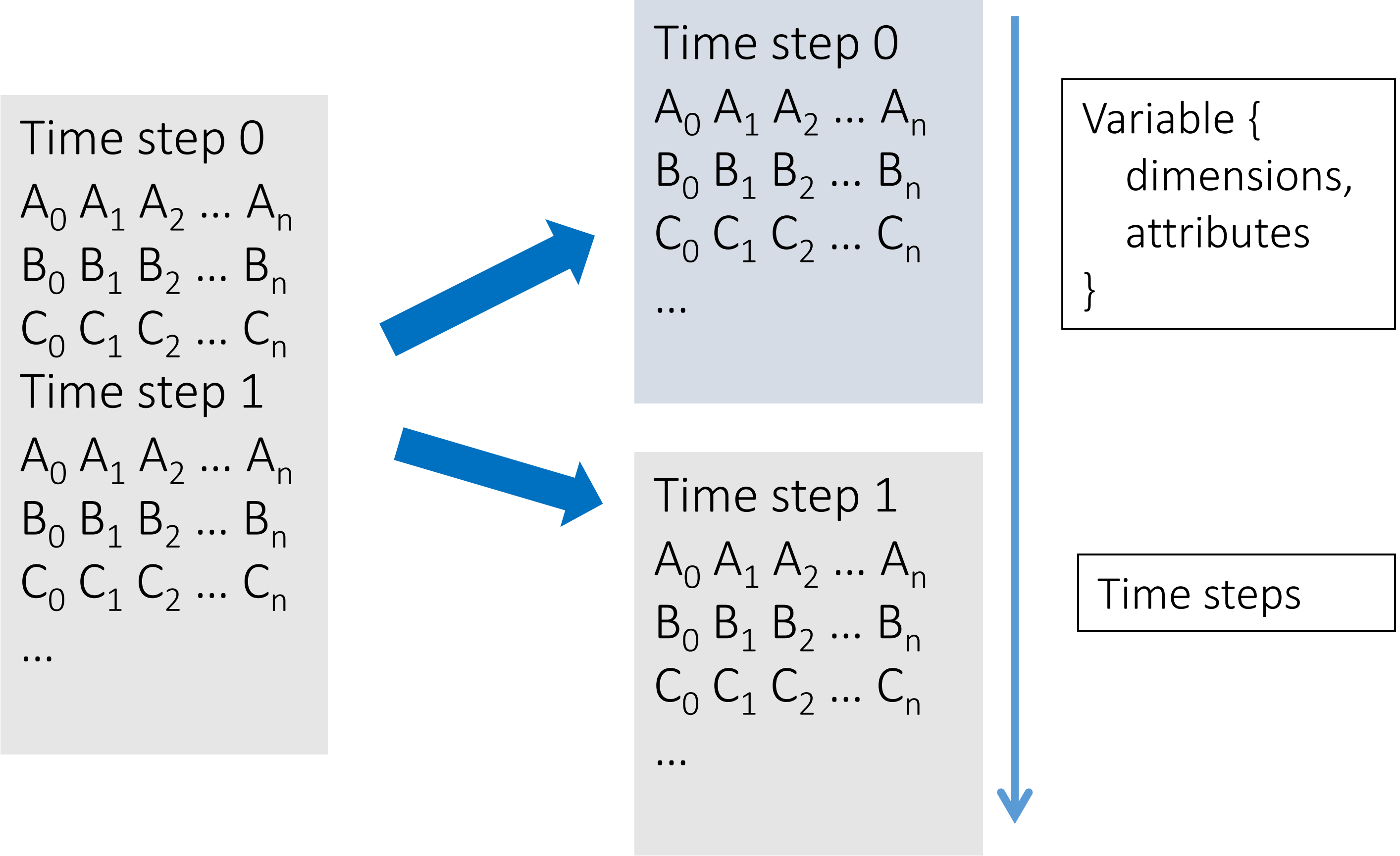

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Time steps

Analytics users know what can/needs to be filtered

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- Reduce cloud upload/download volumes
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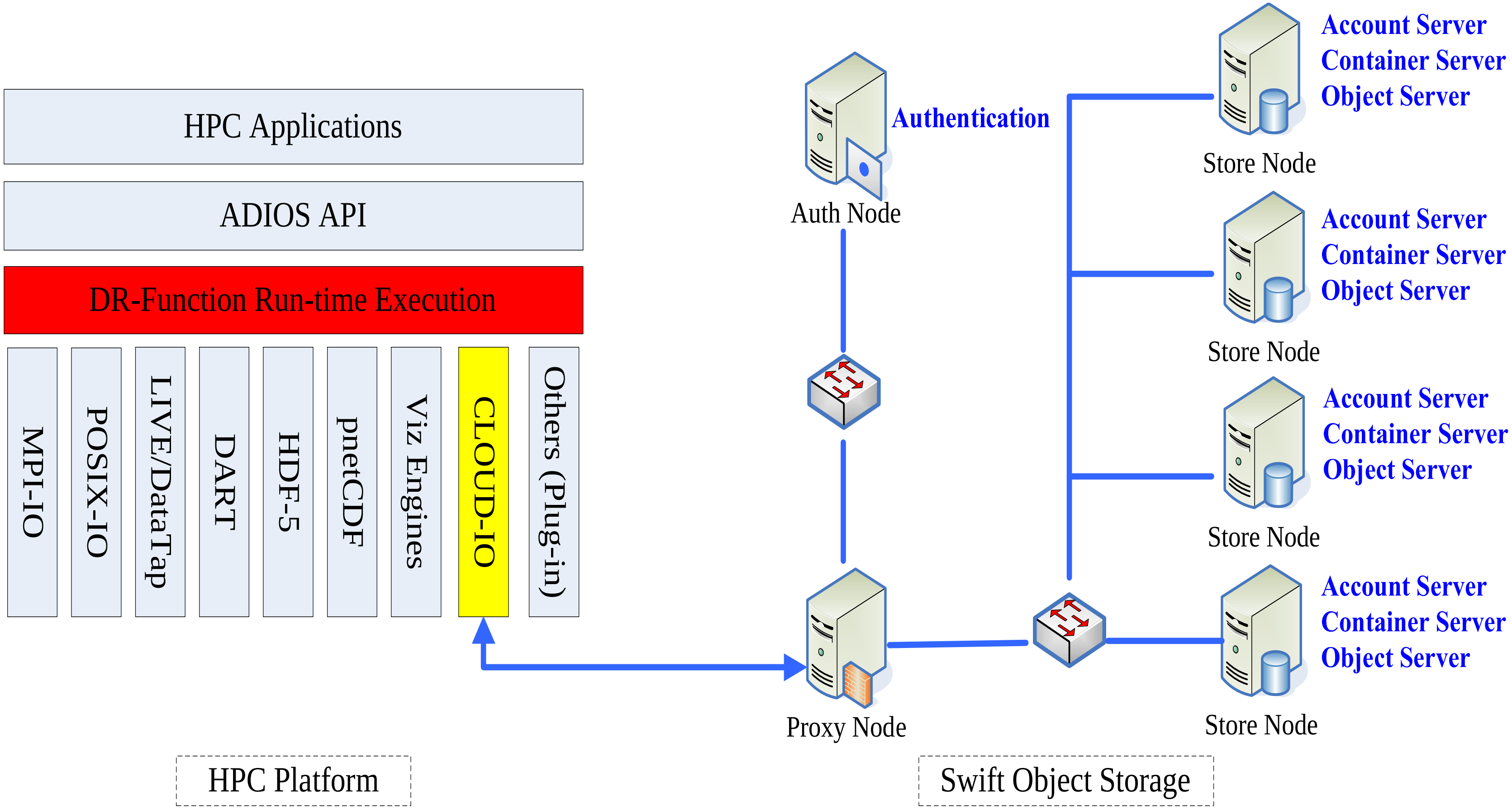
Partial object access for private cloud storage

- Patch the OpenStack Swift object store

Cloud-IO Transport



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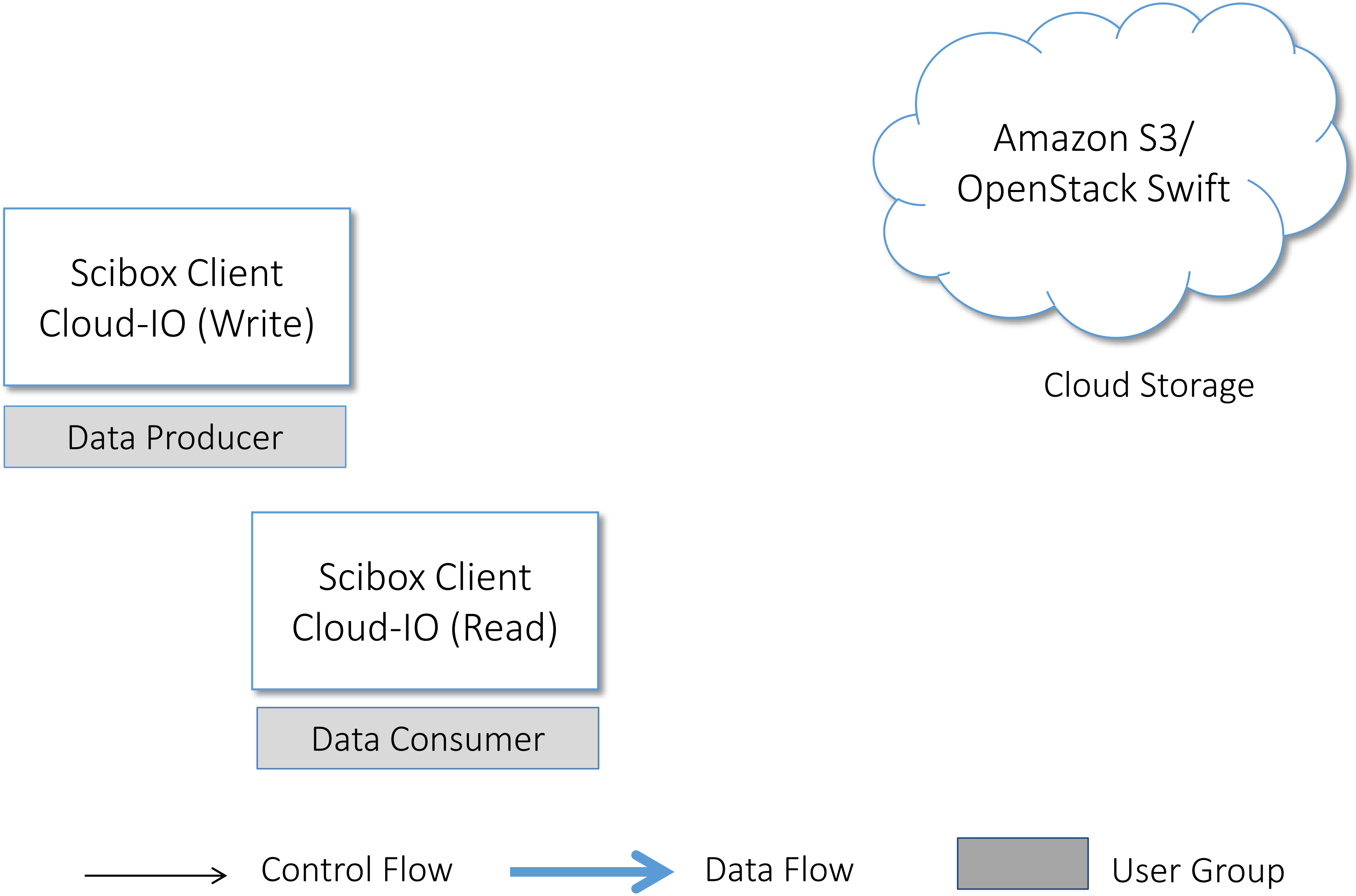


Amazon S3/ OpenStack Swift

Cloud Storage

Scibox Client Cloud-IO (Write)

Data Producer

Scibox Client Cloud-IO (Read)

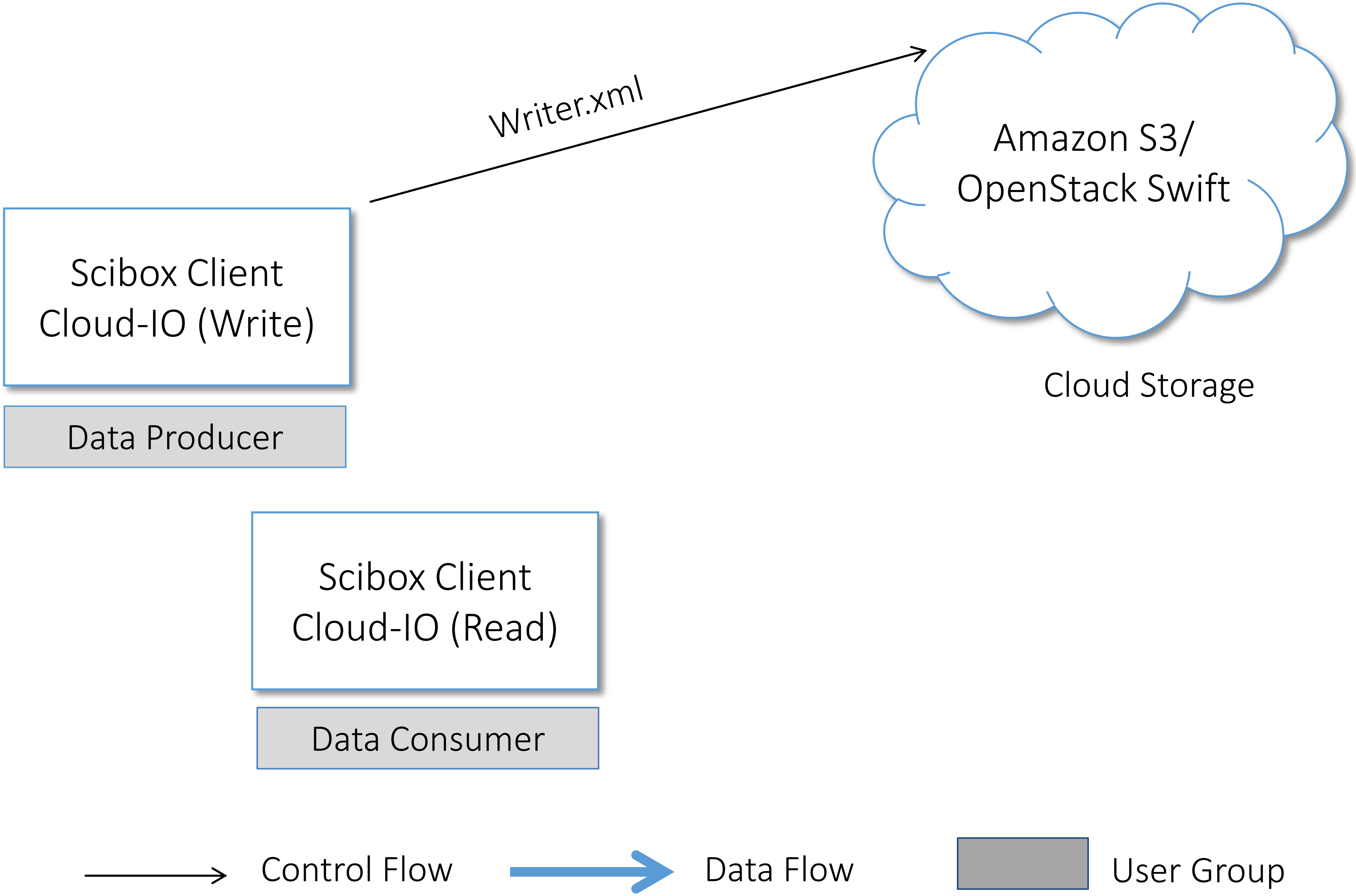
Data Consumer

Control Flow

Data Flow

User Group

Scibox Architecture



Writer.xml

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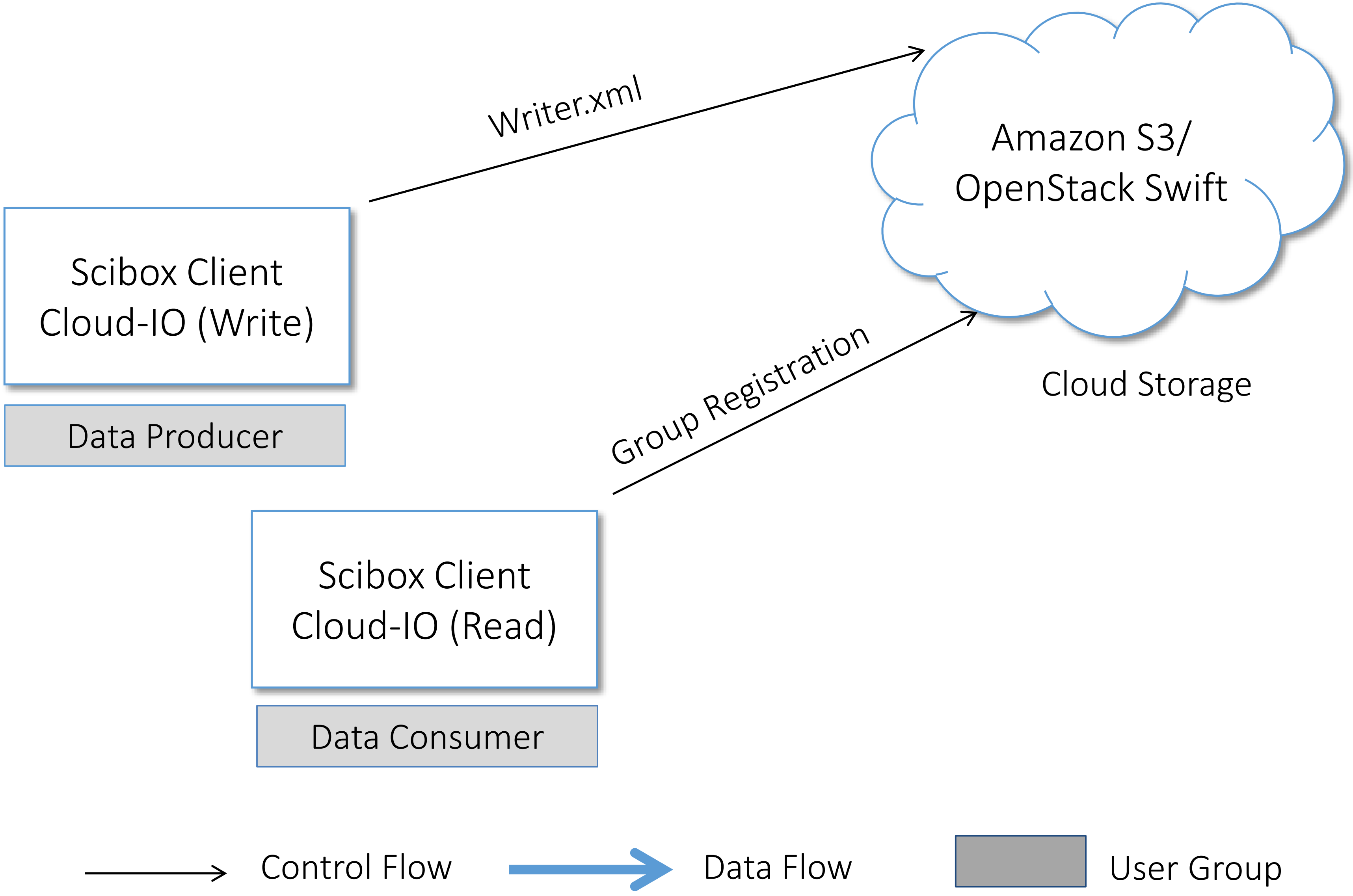
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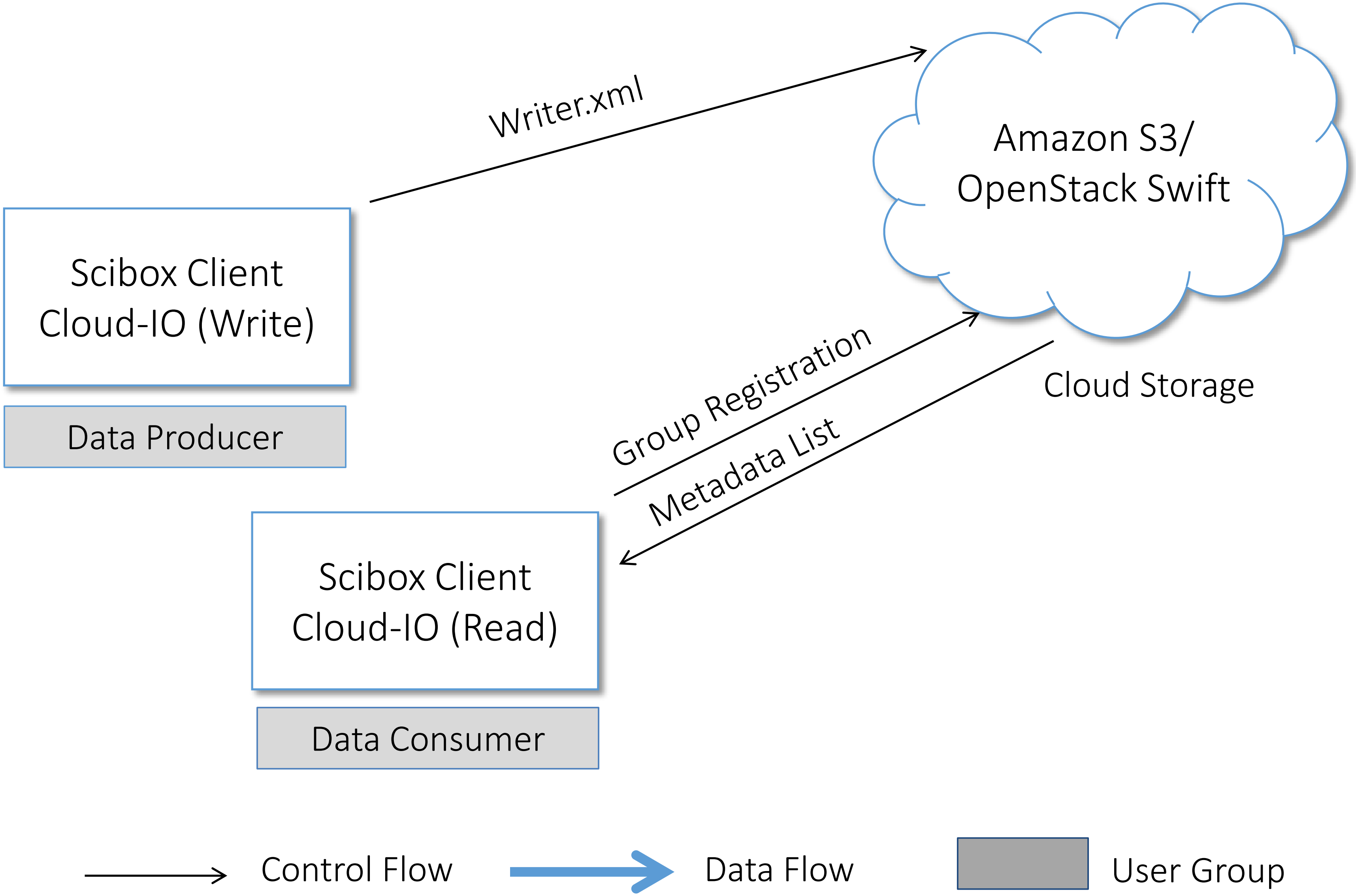

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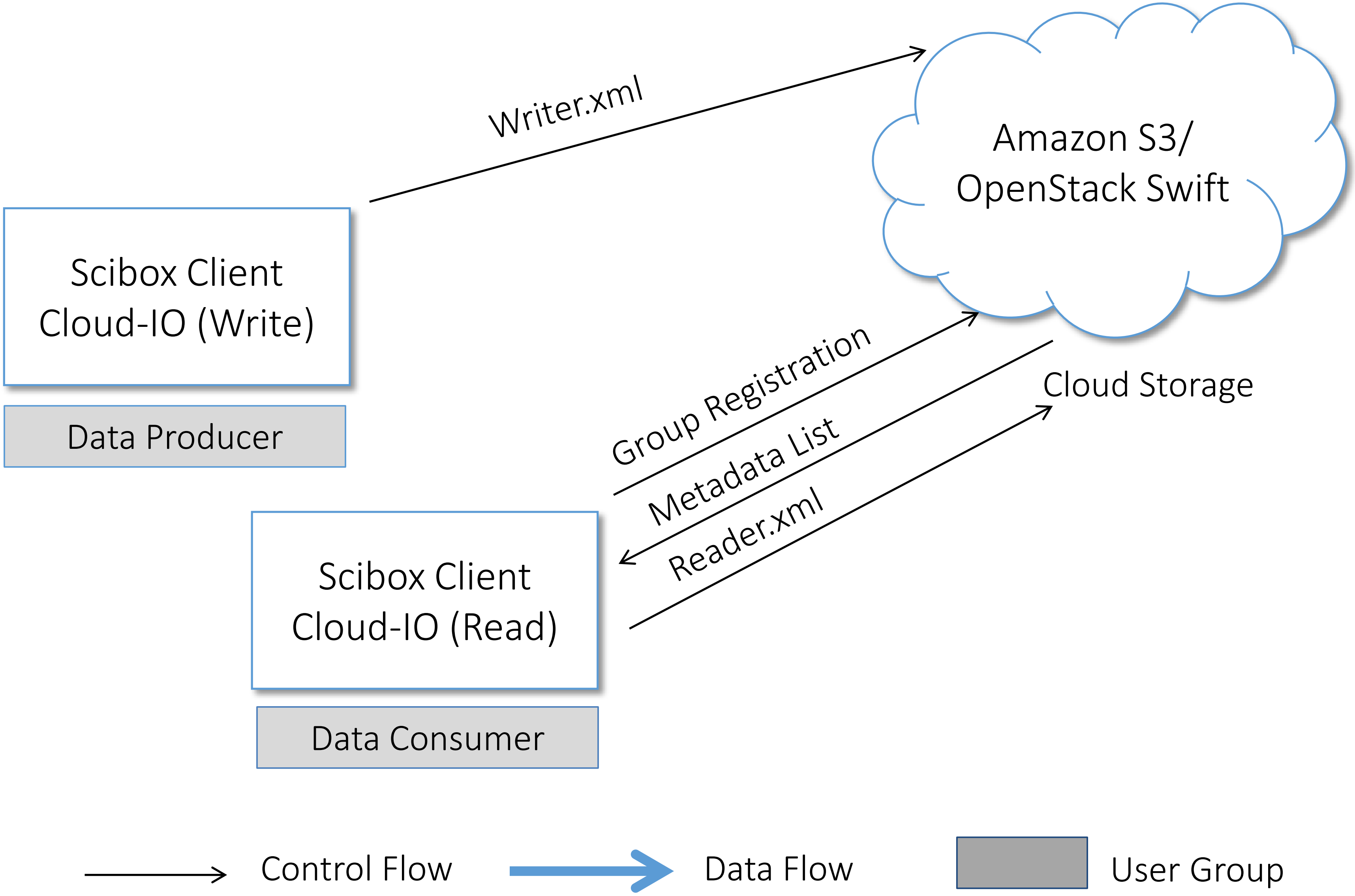

Writer.xml

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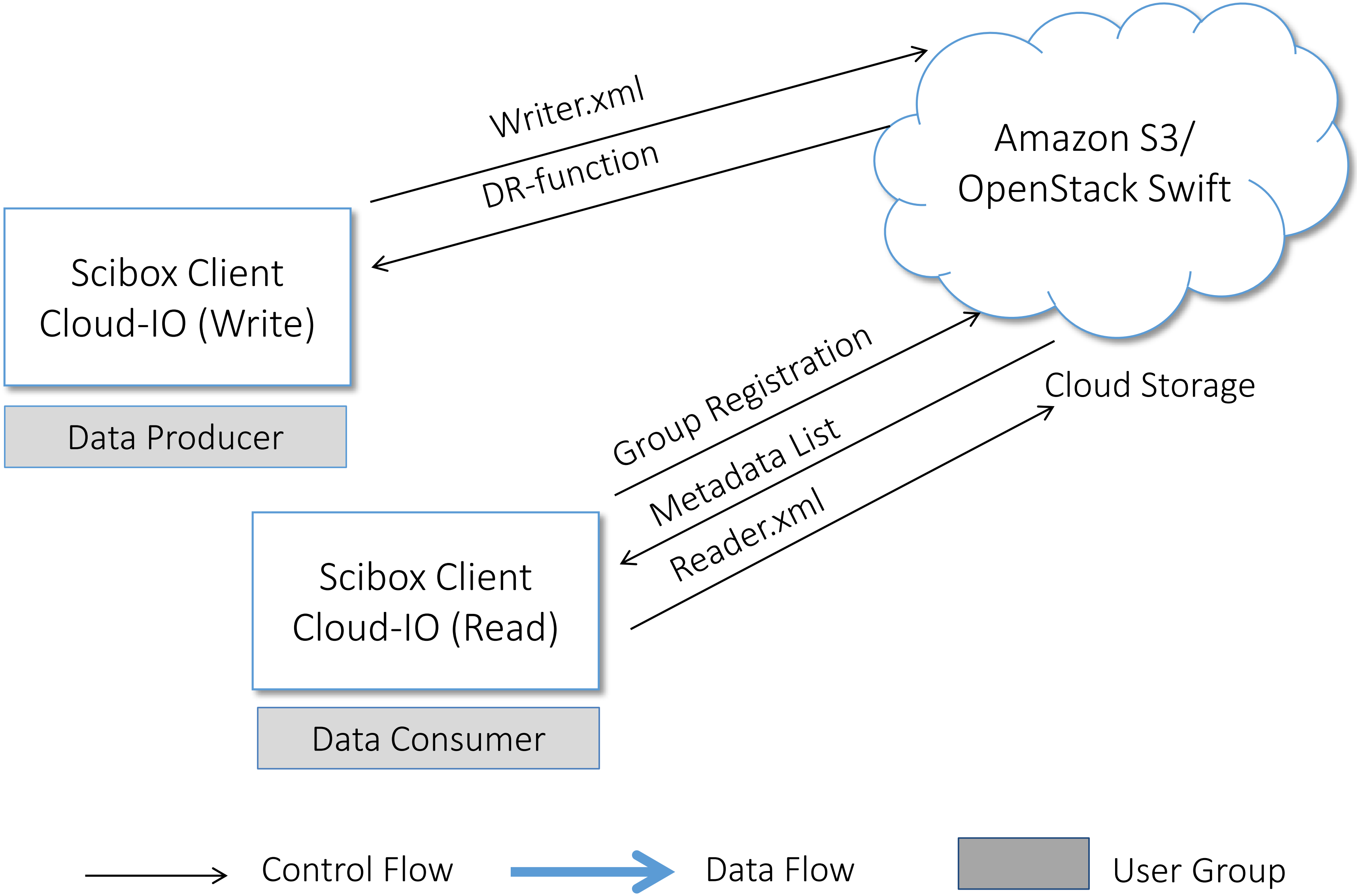

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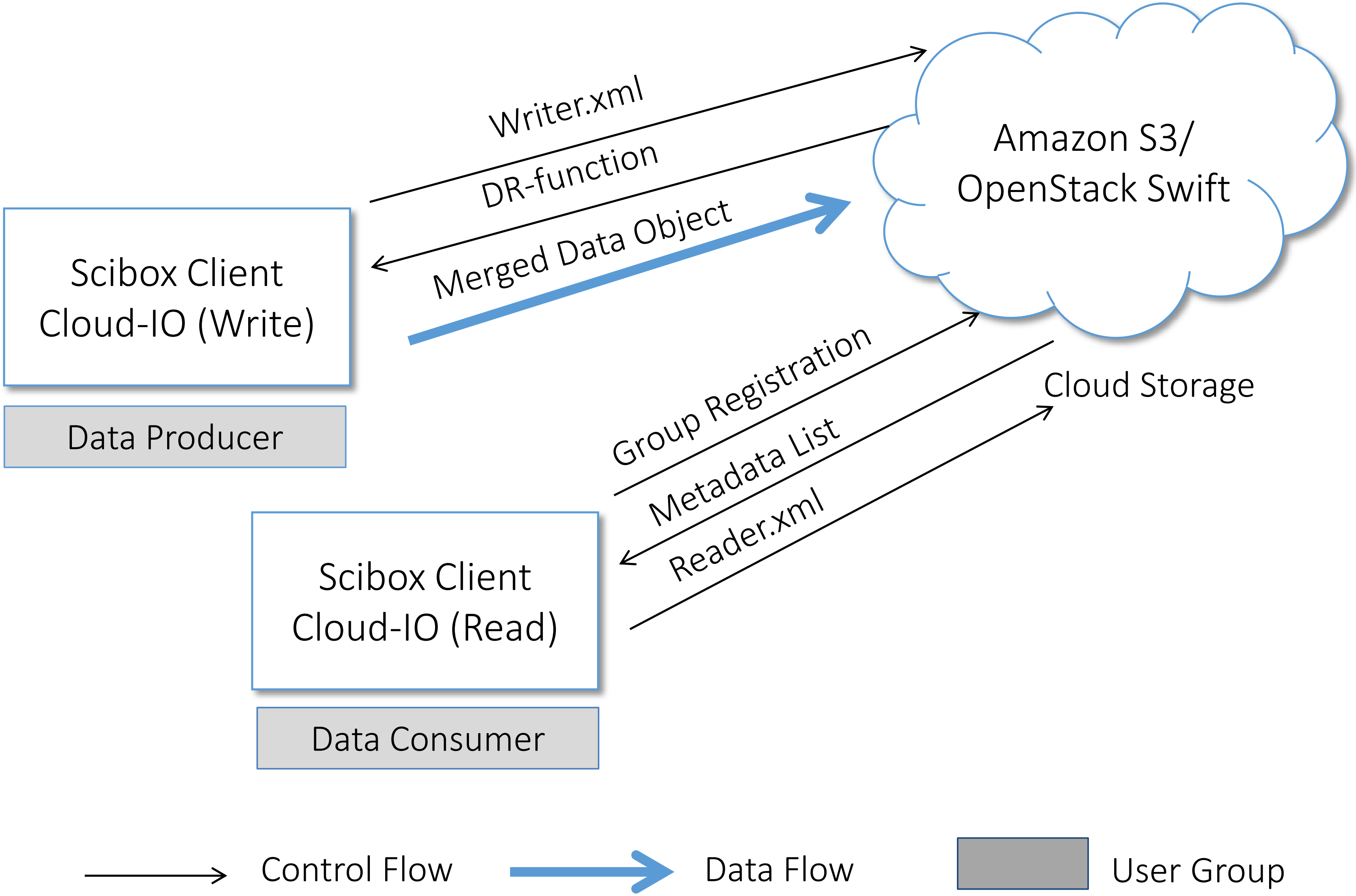

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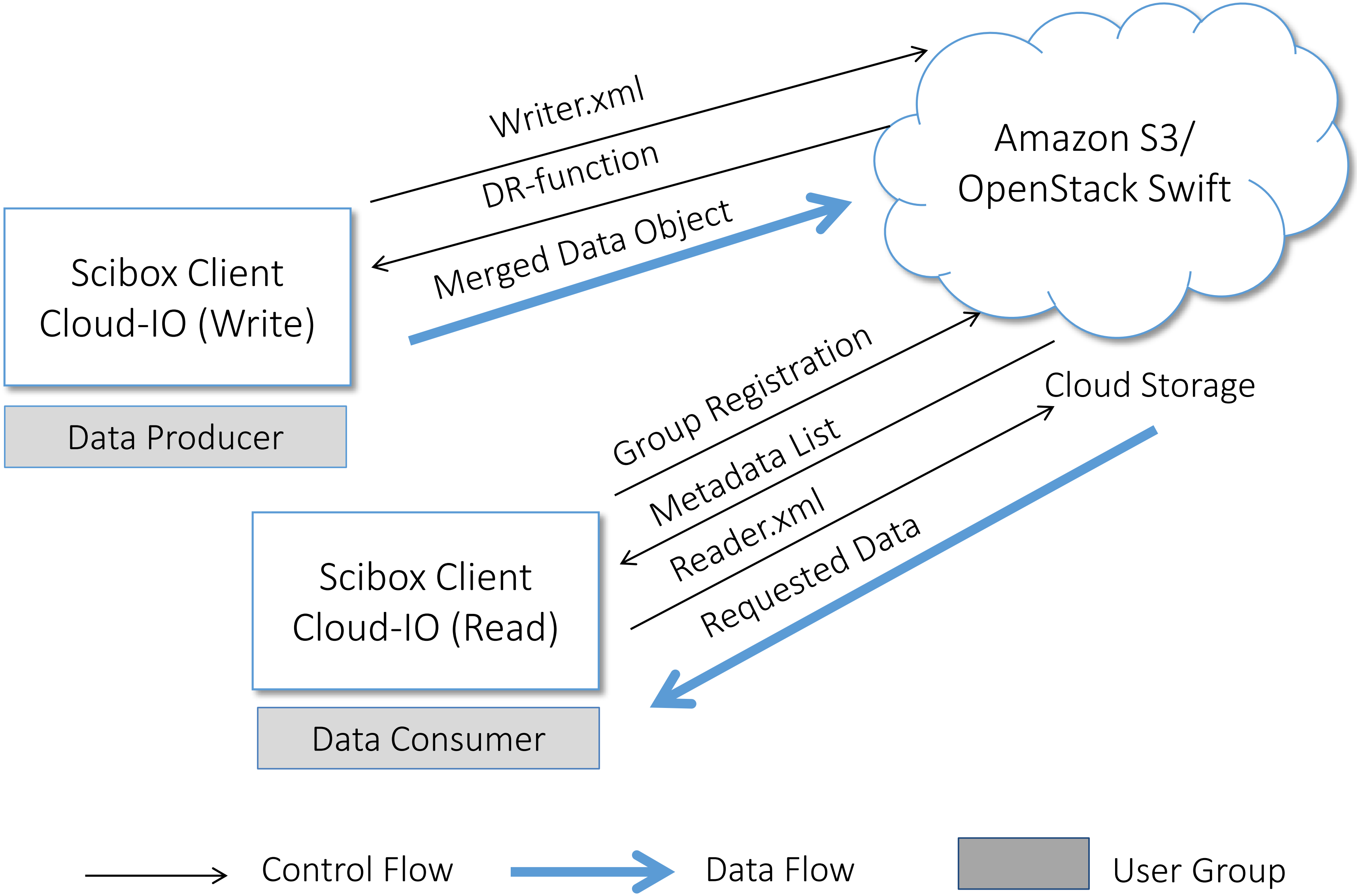

Sample XML File

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    <var name="NX" type="integer"/>
    <var name="NY" type="integer"/>
    <var name="zion0_1Darray"  gwrite="zion0"  type="double"
        dimensions="MIMAX_VAR”/>
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          <!– for reader.xml -->




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                    for(i = 0; i<input.count; i= i+1)
                    { sum = sum + input.vals[i]; }
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Data Reduction (DR) Functions

Definition

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Current implementation

- Customized CoD (C on Demand)

  require producer-side computational resources

- DR-function library

  same DR-function specified by multiple clients, will be executed only once, and its output data will be reused for multiple consumers

DR-functions Provided by SciBox

Type	Description	Example
DR1	Max(variable)	Max(var_double_2Darray)
DR2	Min(variable)	Min(var_double_2Darray)
DR3	Mean(variable)	Mean(var_double_2Darray)
DR4	Range(variable, dimension, start_pos, end_pos)	Range(var_int_1Darray, 1, 100, 1000)
DR5	Select(variable, threshold1, threshold2)	Select var.value where var.value in (threshold1, threshold2)
DR6	Select(variable, DR_Function1, DR_Function2)	Select var.value where var.value ≥ Mean(var)
DR7	Select(variable1, variable2, threshold1, threshold2)	Select var2.value where var1.value in (threshold1, threshold2)
DR8	Self defined function	Double proc(cod_exec_context ec, input_type * input, int k, int m) {int l; intj; double sum = 0.0; double average=0.0; for(i=0;i<m;i++)sum+=input.tmpbuf[i+k*m];average=sum/m; resturn average;}

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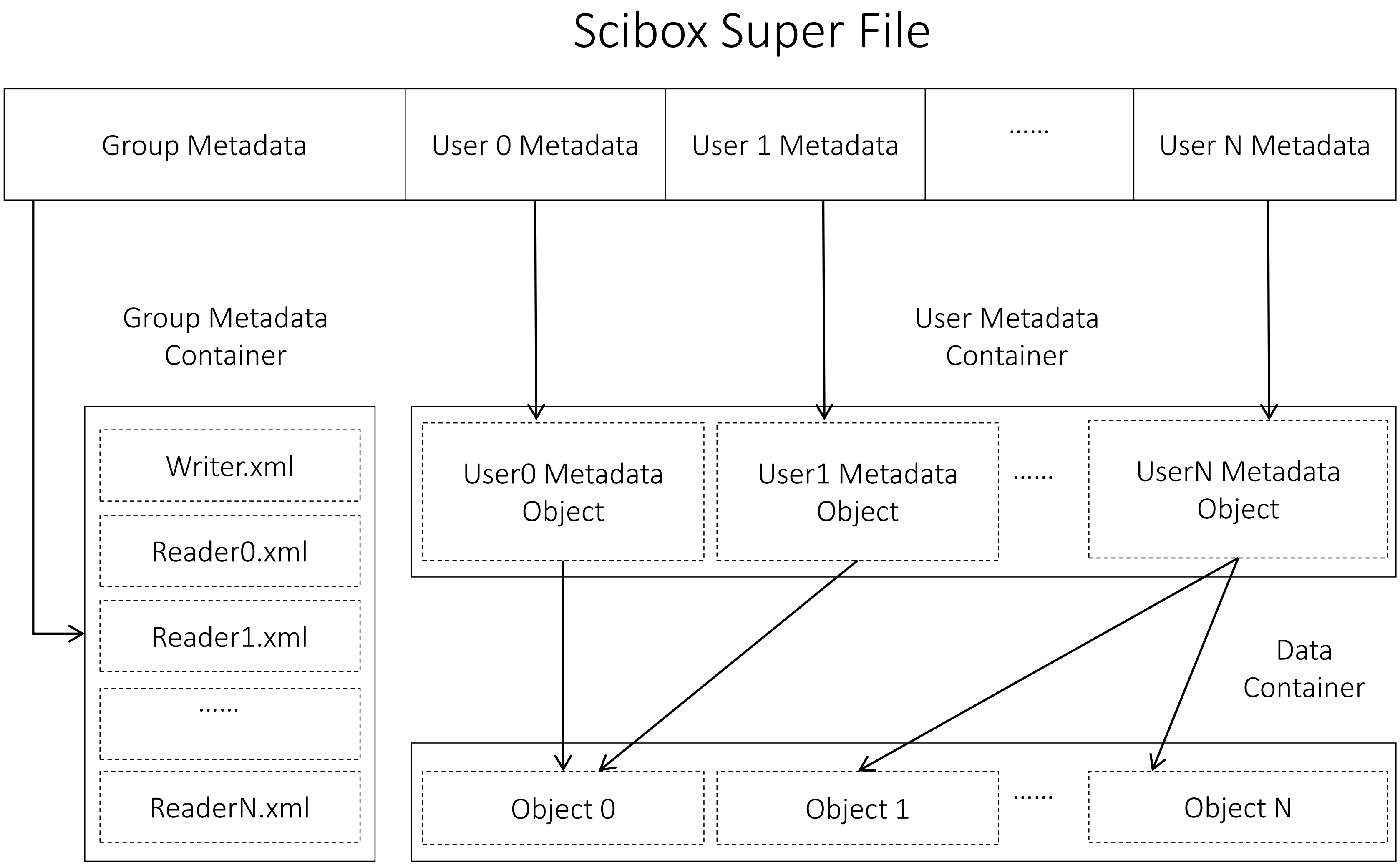
C on Demand (CoD):
Consumer: a string
Producer:
1. registration
2. compile and execute on demand.

Data Object Management



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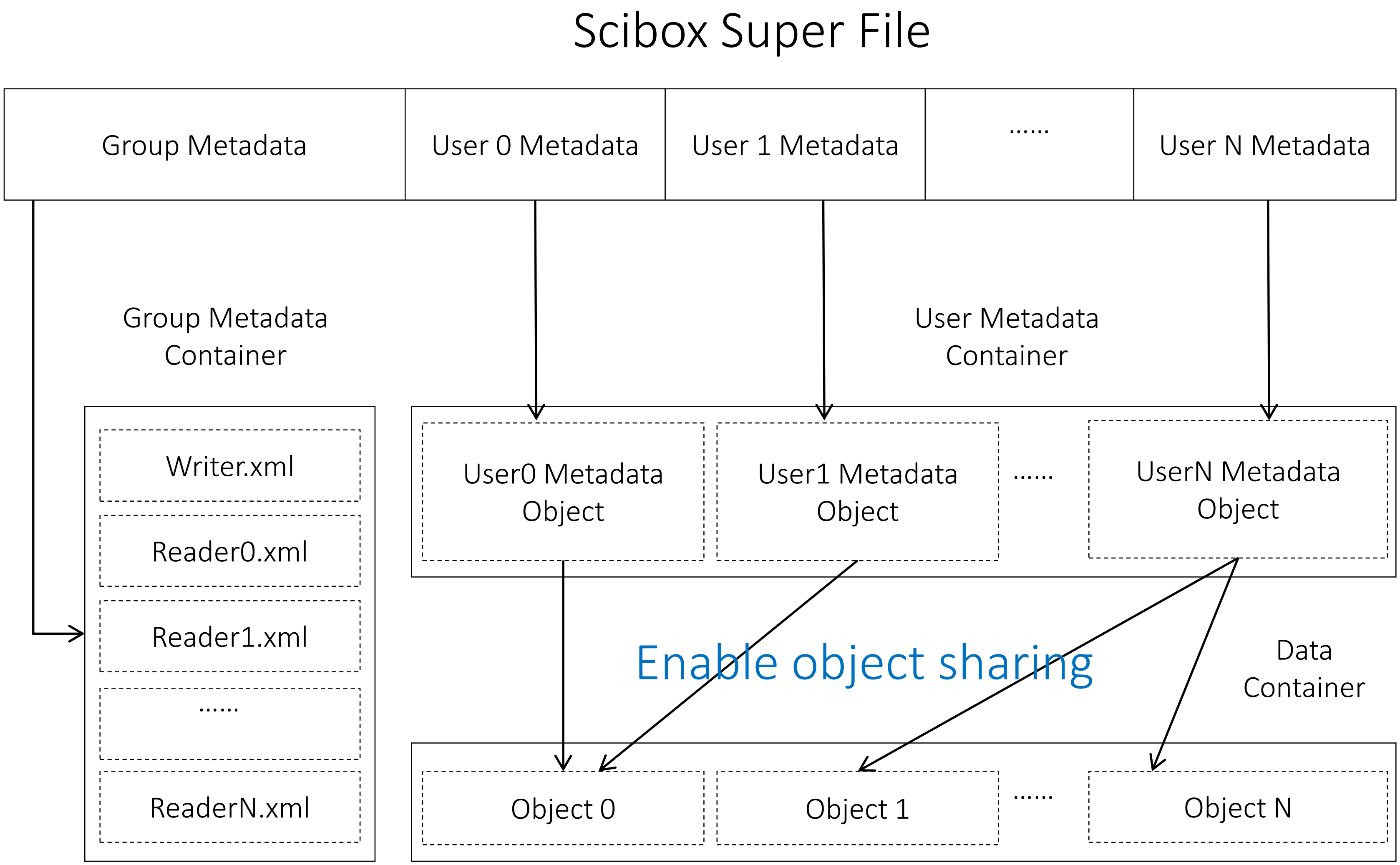

Determination of Object Size

Merge overlapping data sets

- reduce upload data size

Partial object access

- Current Amazon S3 and OpenStack Swift stores do not support this
- Users have to download the whole object, even if only a small portion of its data is needed

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- Current Amazon S3 and OpenStack Swift stores do not support this
- Users have to download the whole object, even if only a small portion of its data is needed

Two approaches used in Scibox

- Private cloud

  modify the software to enable partial object access

  Object size is determined by predicting upload throughput

Determination of Object Size

Merge overlapping data sets

- reduce upload data size

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Two approaches used in Scibox

- Private cloud

  modify the software to enable partial object access

  Object size is determined by predicting upload throughput

- Public cloud

  limit object size considering storage pricing

  Object size is determined by comparing the cost w/ sharing and w/o sharing

Cost Model

Definition

α: $/GB of standard cloud storage

β: $/GB of data transfer into cloud

γ: $/GB of data transfer out from cloud

Assumption

n clients request Data_1, Data_2, … Data_n respectively

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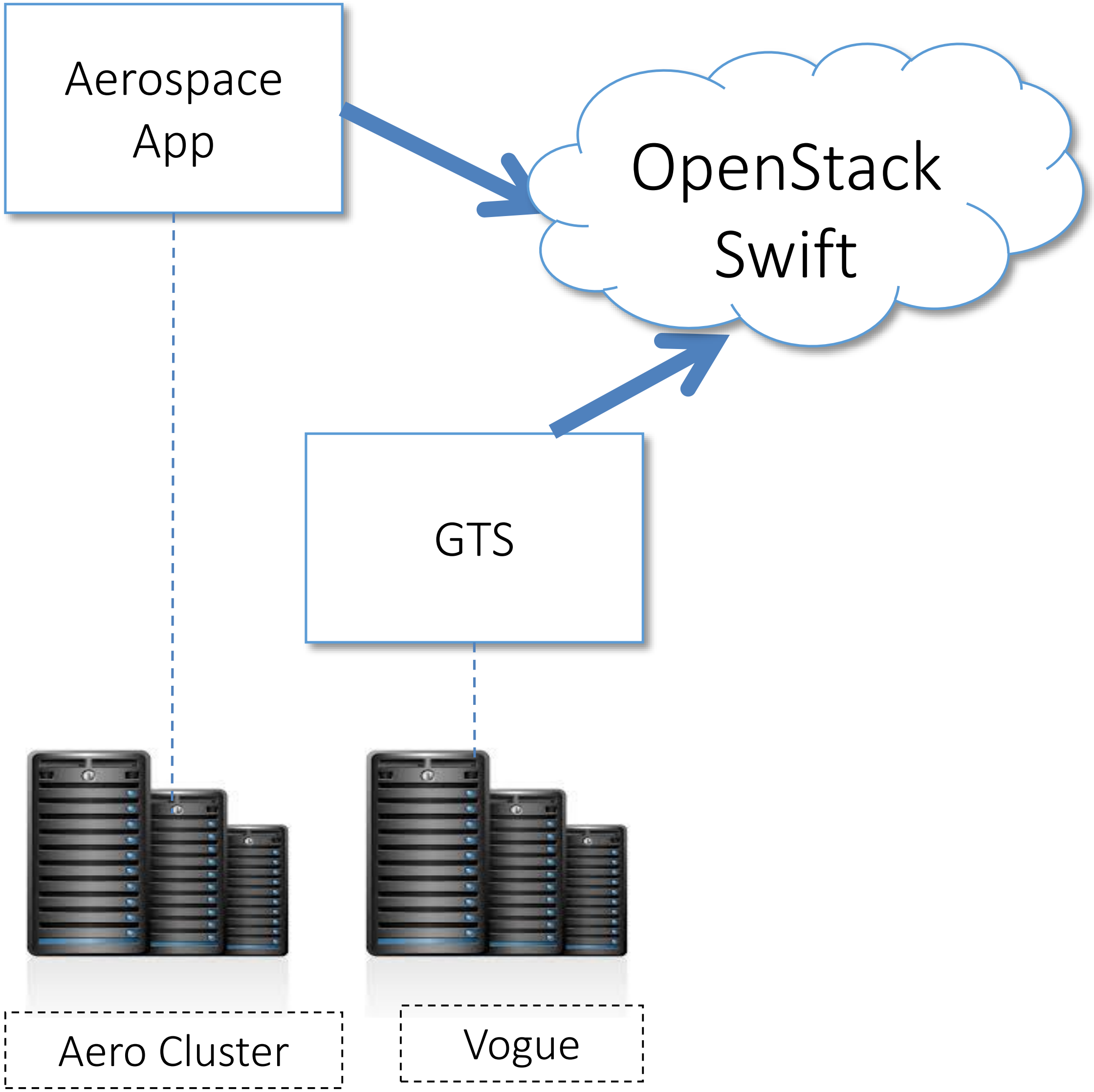
$$Size \leq \frac{(\alpha + \beta + \gamma) * \sum_{i=1}^{n} Data_i}{\alpha + \beta + n\gamma}$$

Outline

- Background and Motivation
- Problems and Challenges
- Design and Implementation
- Evaluation
- Conclusion and Future Work

Experimental Setup



Aerospace App

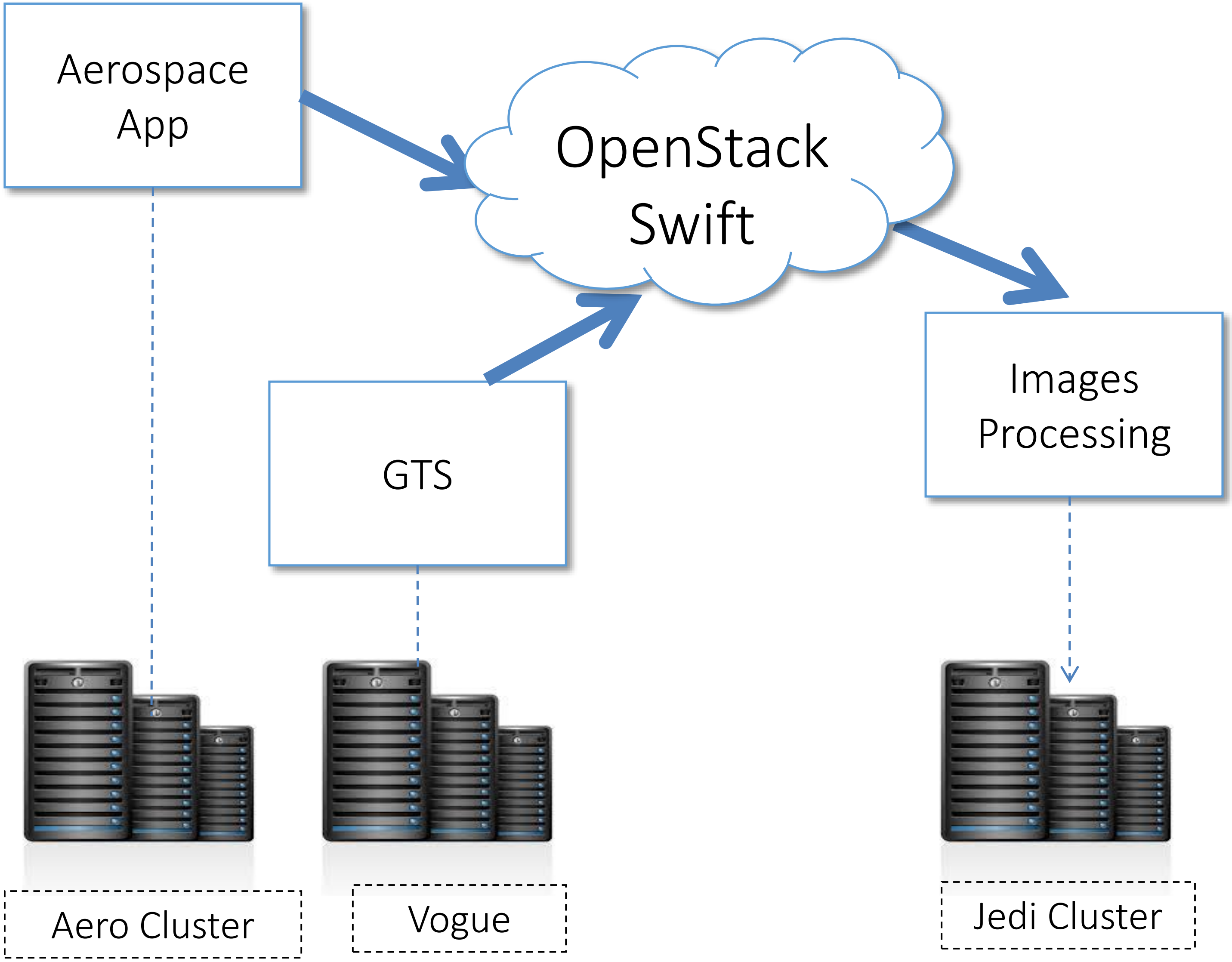
OpenStack Swift

GTS

Aero Cluster

Vogue

Experimental Setup



Aerospace App

OpenStack Swift

GTS

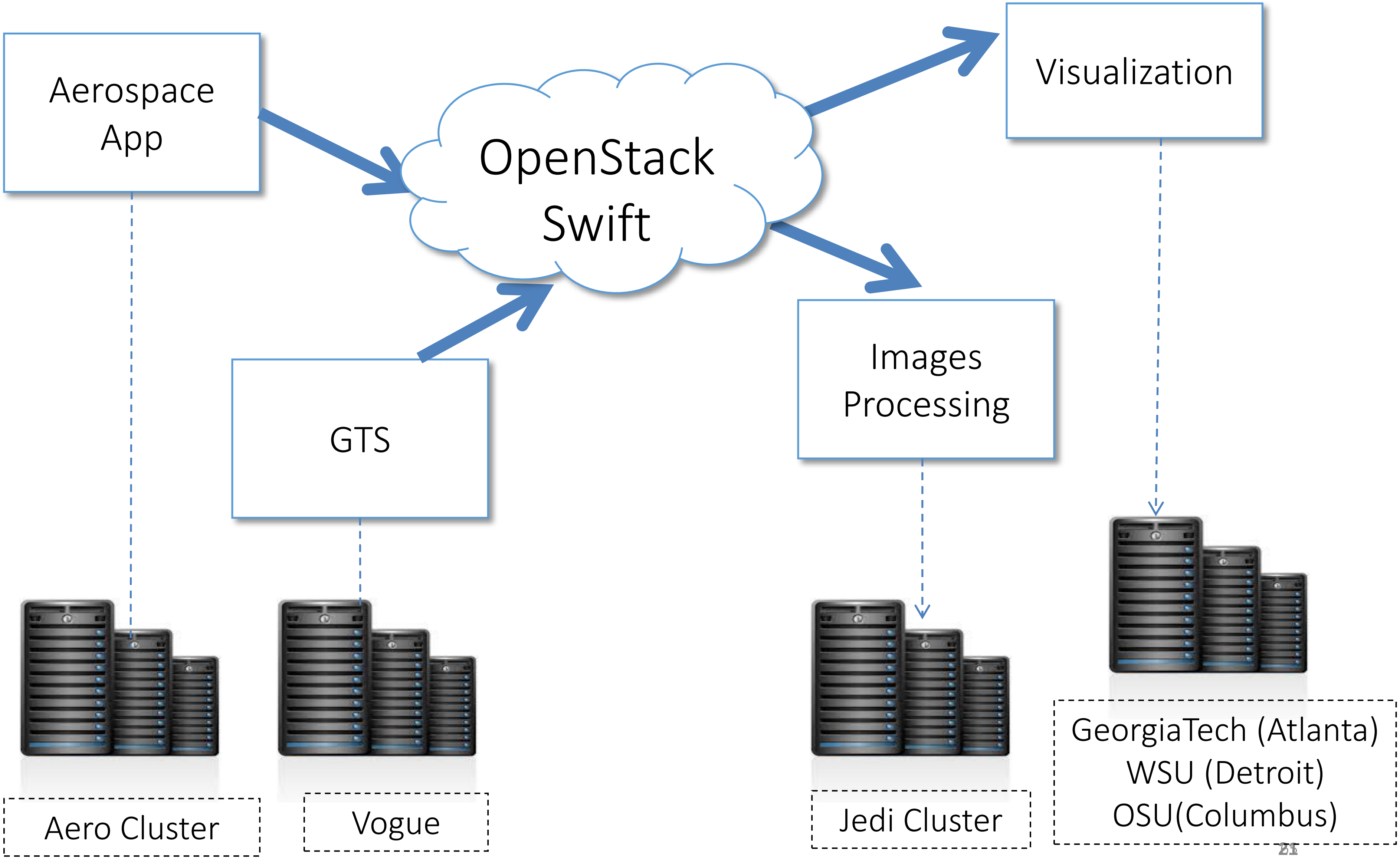
Images Processing

Aero Cluster

Vogue

Jedi Cluster

Experimental Setup



Aerospace App

GTS

OpenStack Swift

Visualization

Images Processing

Aero Cluster

Vogue

Jedi Cluster

GeorgiaTech (Atlanta)
WSU (Detroit)
OSU(Columbus)

Workloads

Synthetic Workloads

- 10 variables shared by multiple consumers
- 1,000 requests generated by each consumer
- 8 types of DR functions, uniformly distributed
- 1 data producer serving 1,000 requests x #client servers
- 3 self-defined DR-functions:

  FFT, histogram diagnosis, and average of row values of a matrix

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Real Workloads

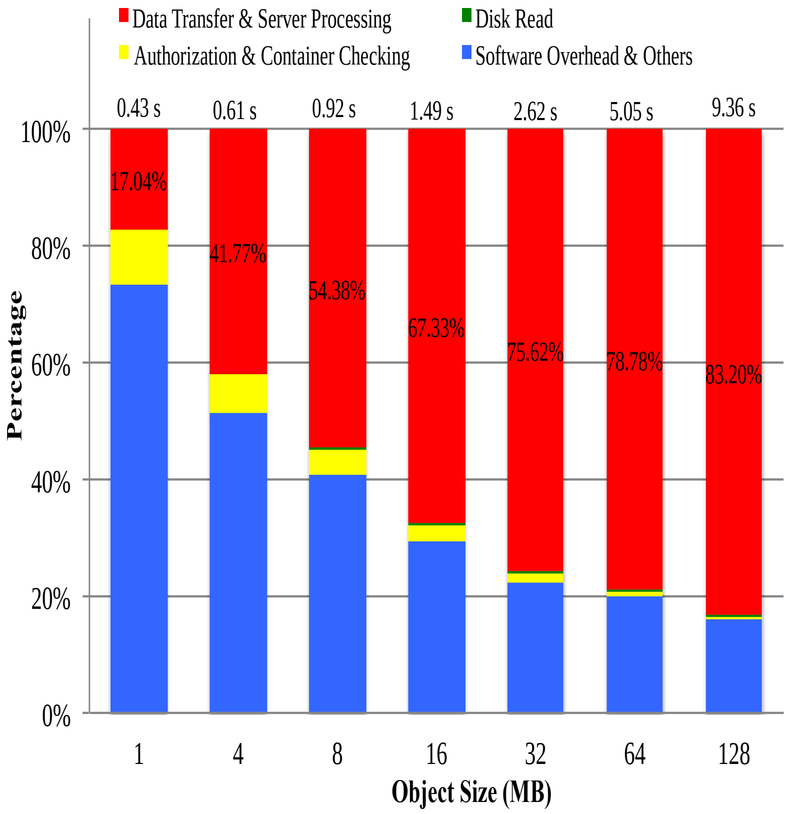
- GTS workload

  128 parallel processes, consumers are from 3 different states in USA

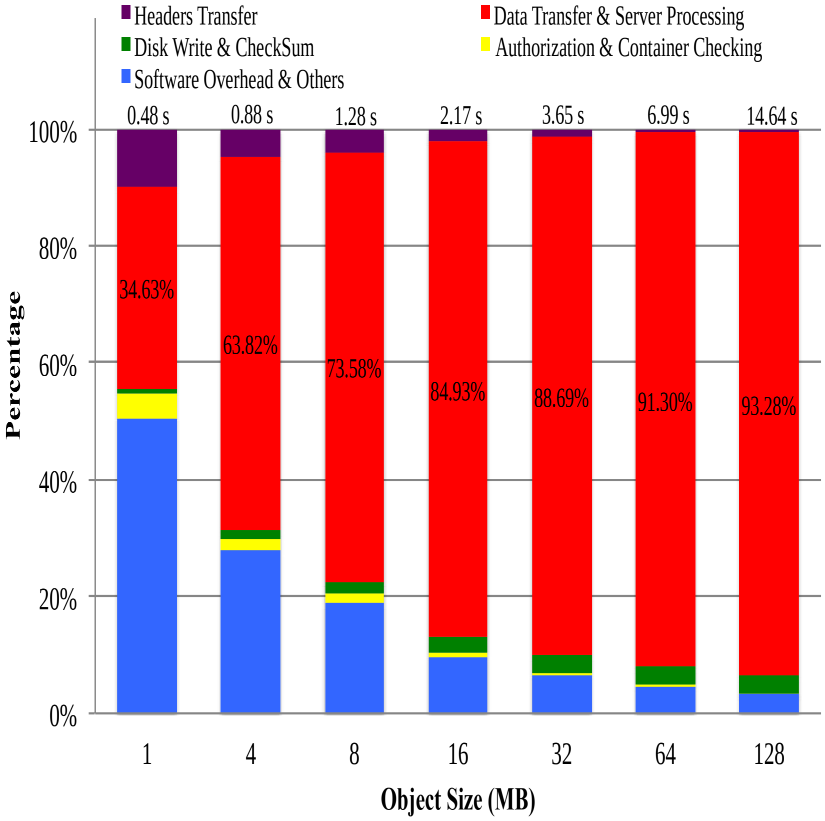
- Combustion workload

  10, 000 512X512 12-bit double framed images (~1.5 MB per image)

Latency Breakdown of Swift Object Store

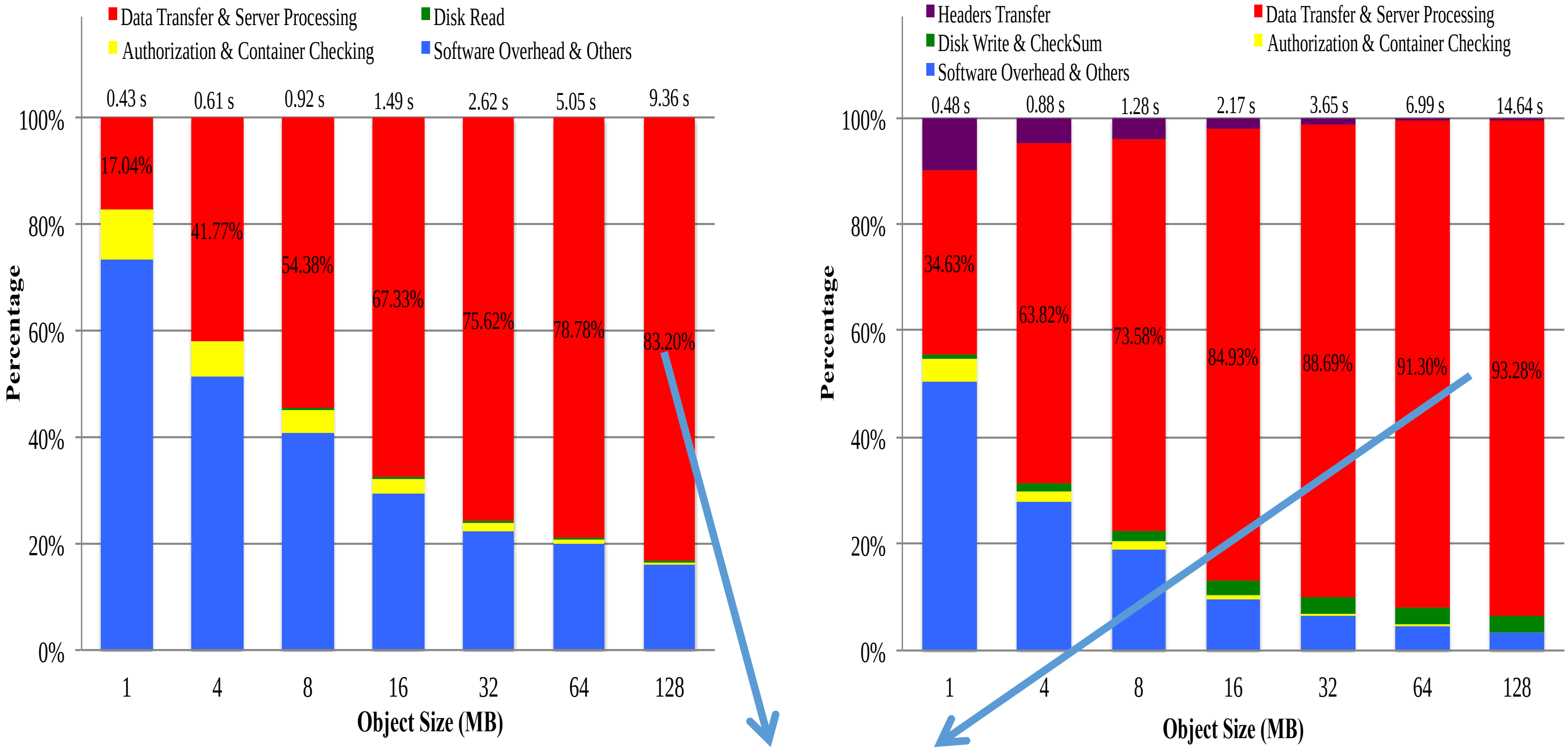


Put



Get

Latency Breakdown of Swift Object Store

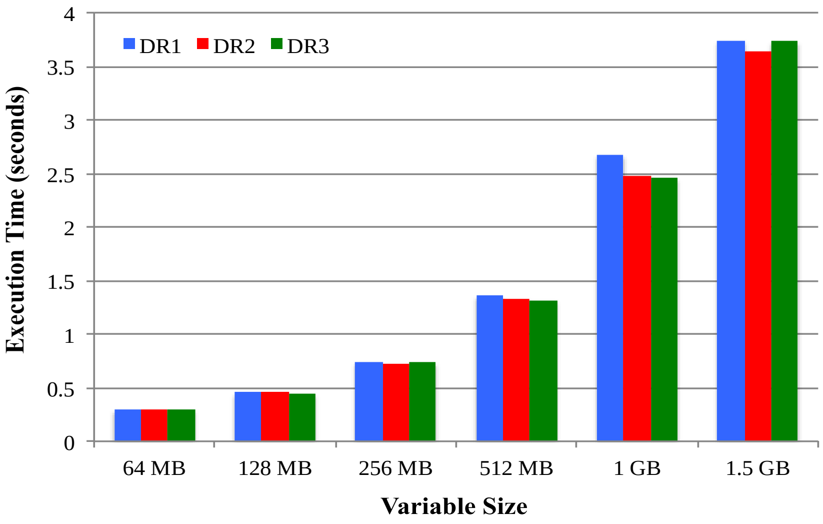


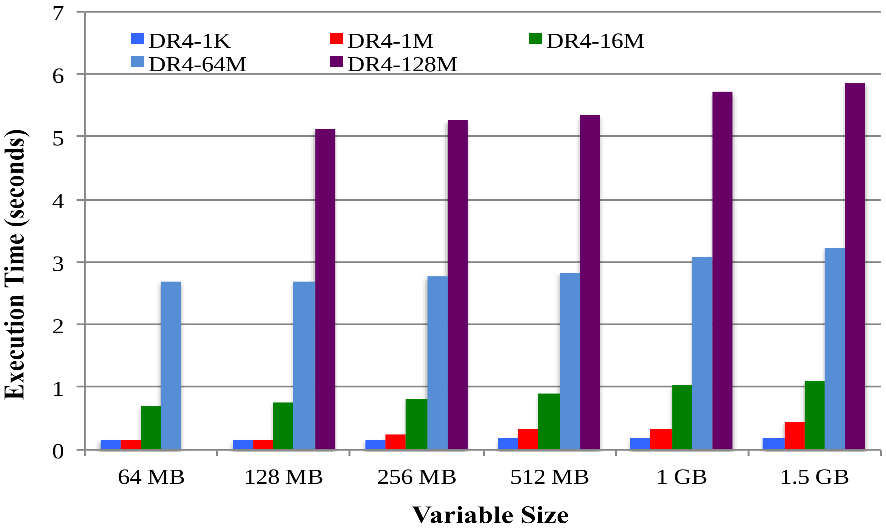
Put

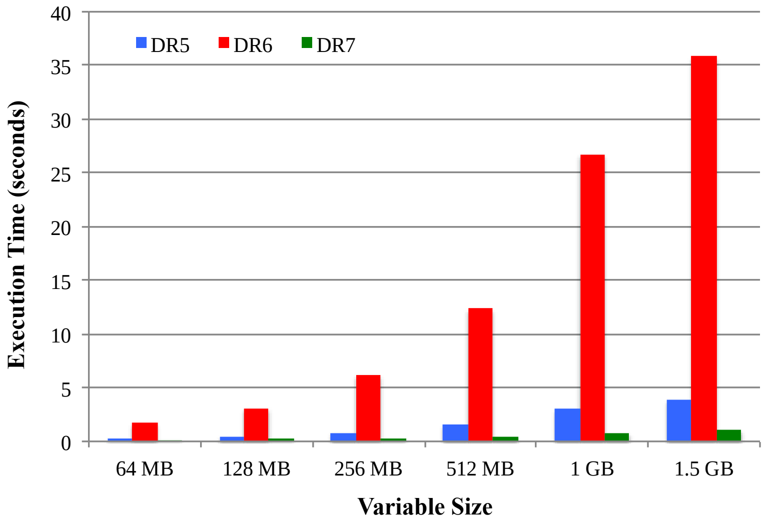
Data transfer dominates the request latency.

Get

Execution Time of DR-functions







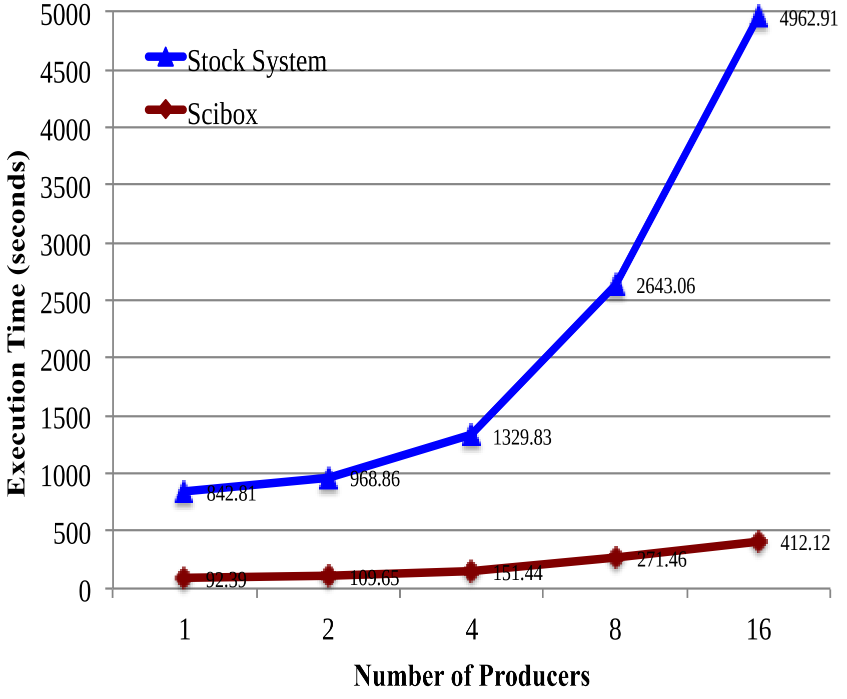
Recall: DR6:var.value where var.value>Mean(var).

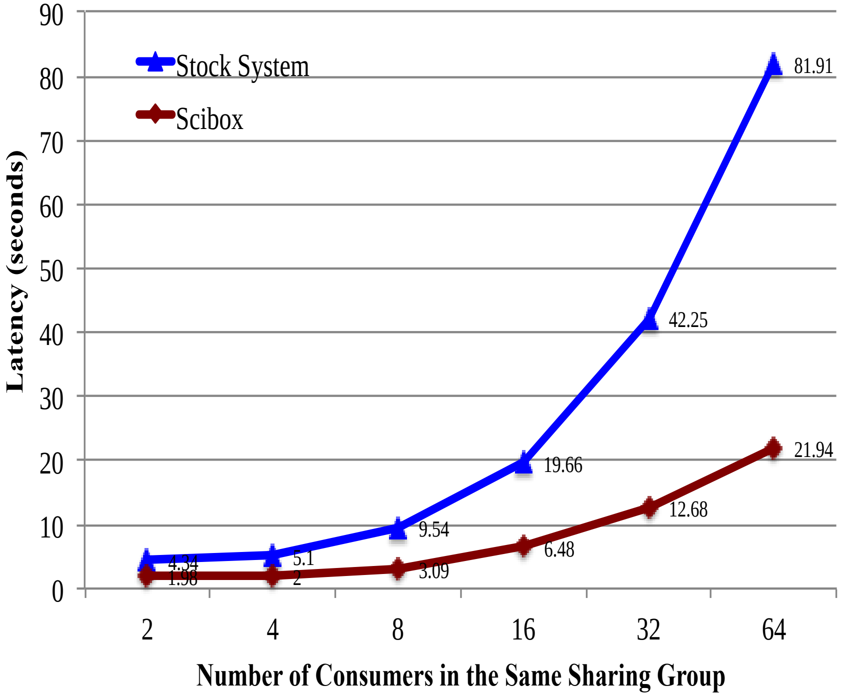
Double scan of input data.

Recall: DR7:Select var2.value where var1.value in (r1, r2).

var1 is small.

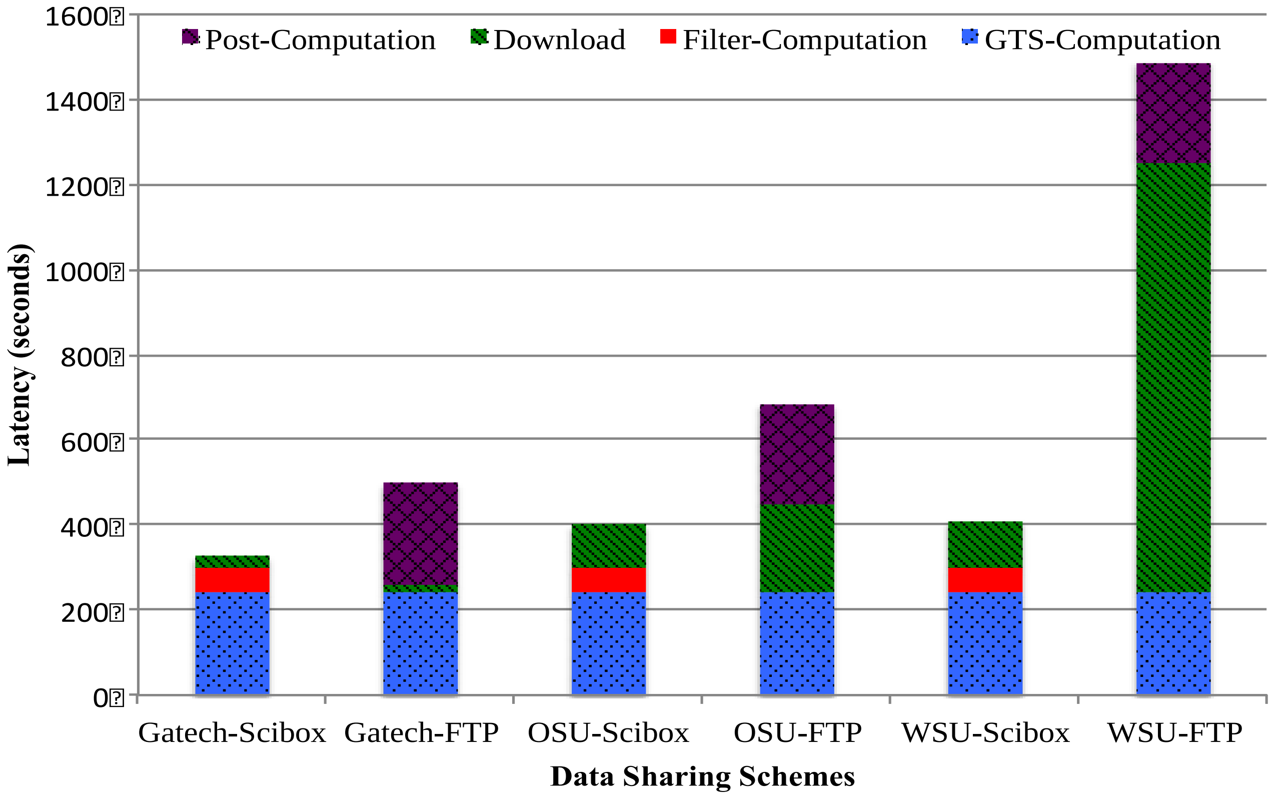
SciBox System Scalability





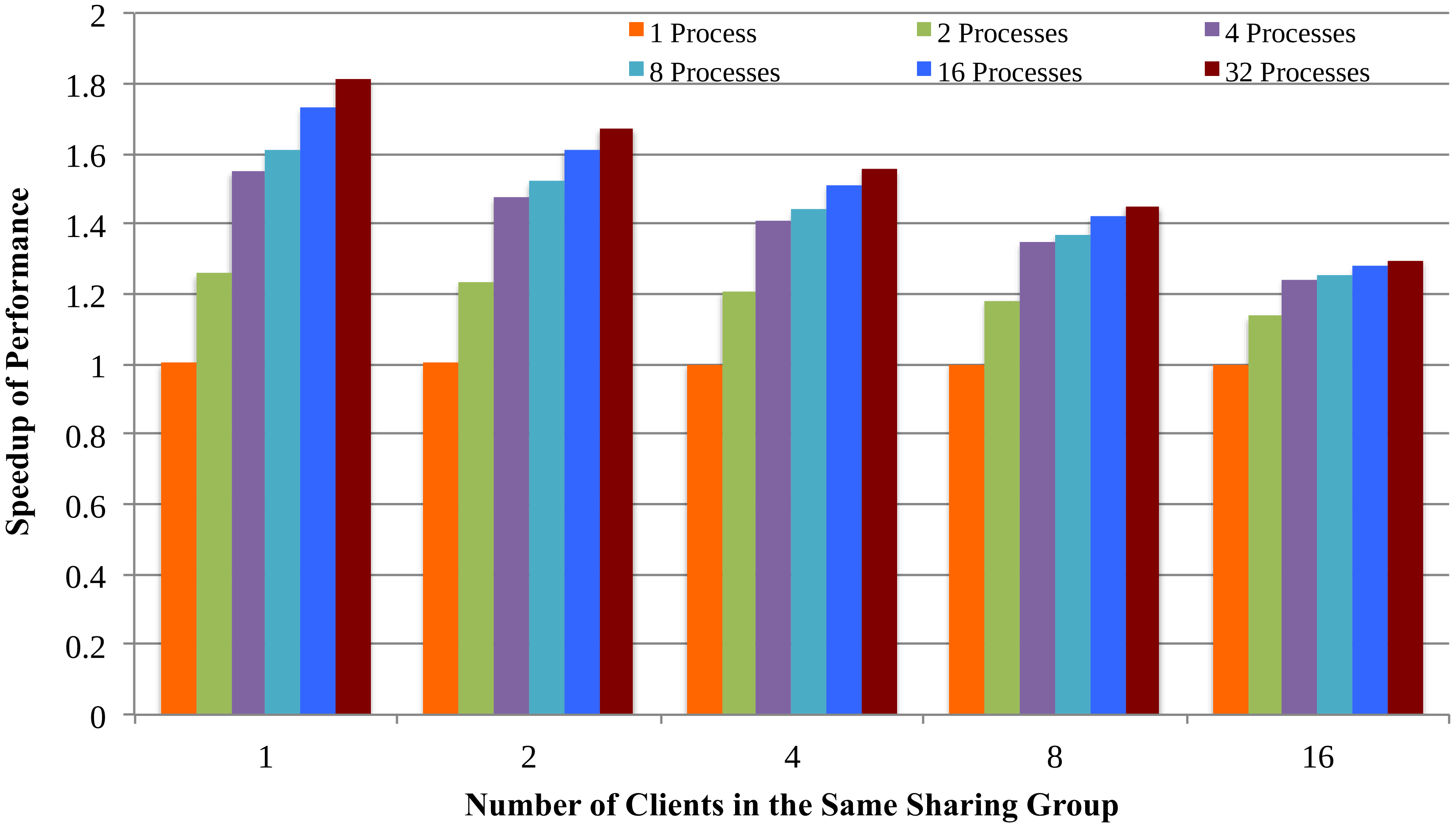
- With Scibox, data is merged before upload
- With Scibox, partial object access is supported

GTS Workload



	WSU	OSU	GT
GT	900 KB/s	4.4 MB/s	44 MB/s

Combustion Workload



- DR-function: (ImageName, DR8, FFT)
- 10, 000 images (~1.5 MB/image) shared via Scibox

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Scibox: Cloud-based support for scientific data sharing

- Can operate across both public and private cloud stores

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Future Work

- Deploy Scibox on national labs' facilities to better understand potential use cases
- Additional optimizations of cloud storage for scientific data management

Thanks!