I/O Characterization of Heterogeneous Workflows

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Overview and Contribution

Workflows:

- ❑ Are pre-defined or random ordered execution of a set of tasks that produce scientific results.
- ❑ Form Directed Acyclic Graphs (DAGs) where the nodes are the tasks and the edges are the inter data-dependencies.
- ❑ Consist of ***heterogeneous stages*** with different system requirements which spawn processes dynamically depending on their needs.

Project goals:

- ❑ To explore **Performance Optimization** opportunities for large-scale workflows.
- ❑ To improve **Resource Management** in High-Performance Computing (HPC) systems

Immediate goals:

- ❑ To investigate into the different requirements of heterogeneous workflows.
- ❑ To identify **Performance bottlenecks** in workflows.

Our **contributions** are:

- ❑ We analyze the run-time and perform a systematic **characterization** for three workflows.
- ❑ We identify stages that **have higher I/O bandwidth requirement,** are heterogeneous and can benefit from **Dynamic Resource Scheduling**.

Methodology

1. Workflow Source code annotation to trace Application calls
2. Calls are translated into `events` and stored into trace files of GB of size
3. Traces are loaded and analyzed using *dask distributed framework* and queries.

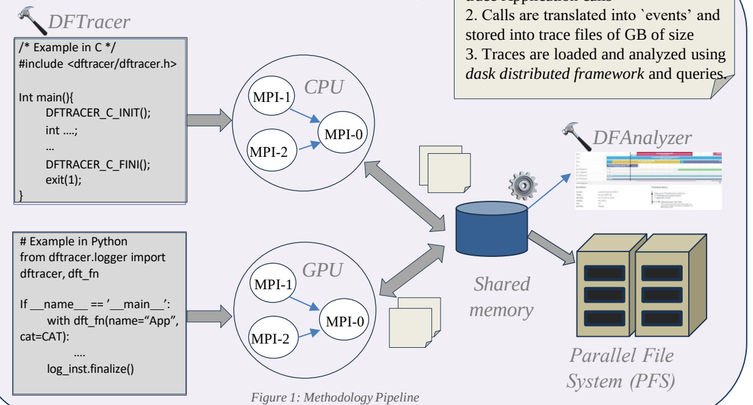


Figure 1: Methodology Pipeline

Workflow	LC Cluster	Nodes	Process per node	Input	How	Computing Element	PFS	Code	DFTracer Overhead
Montage [1]	Corona	32	48	2MASS survey	Flux, MPI	AMD Rome CPU	Lustre	C	7%
1000 Genome [2]	Corona	32	48	10 chromosomes from IGRS [4]	Flux, Pegasus Workflow Manager [5]	AMD Rome CPU	Lustre	Python	5%
MuMMI [3]	Lassen	32	44	PyTorch model file	Flux, Custom workflow manager	IBM Power9 CPU, NVIDIA V100 GPU	GPFS	C/C++ CUDA Python	<1%

Table I: Software, Hardware and Experimental Set-Up

Runtime Analysis Results

(a) Montage

Total Time	I/O Time	App Time
2hr 27 min	15 min	2hr 22min

Table II: Runtime Analysis of Montage

(b) 1000 Genome

Total Time	I/O Time	App Time
1hr 44min	48min 18sec	1hr 30min

Table III: Runtime Analysis of 1000 Genome

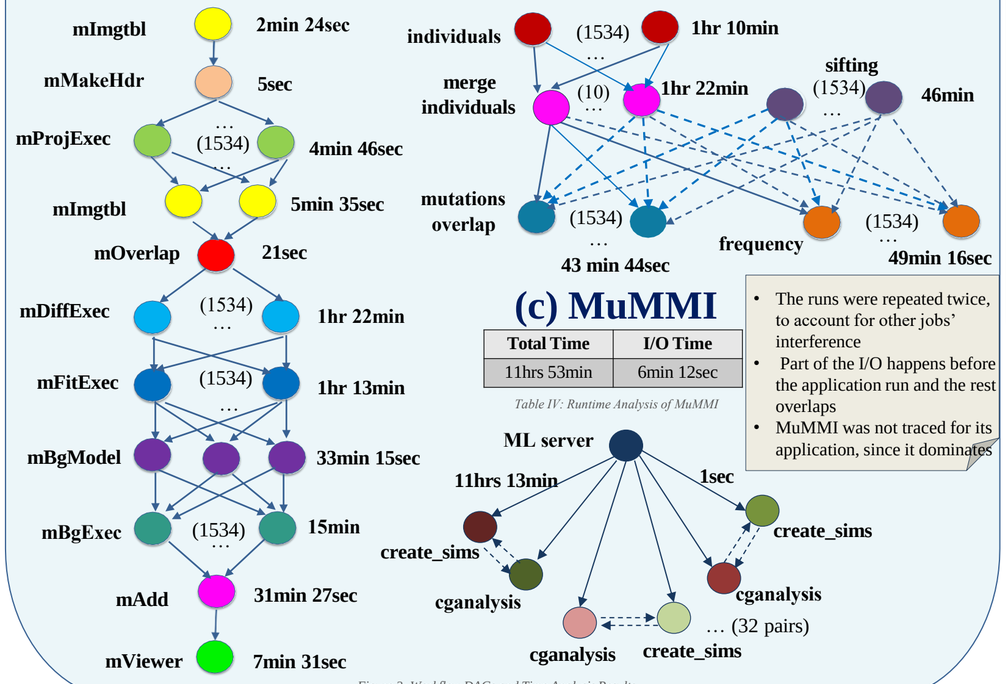


Figure 2: Workflow DAGs and Time Analysis Results

(c) MuMMI

Total Time	I/O Time
11hrs 53min	6min 12sec

Table IV: Runtime Analysis of MuMMI

- The runs were repeated twice, to account for other jobs' interference
- Part of the I/O happens before the application run and the rest overlaps
- MuMMI was not traced for its application, since it dominates

Scheduling and Bandwidth

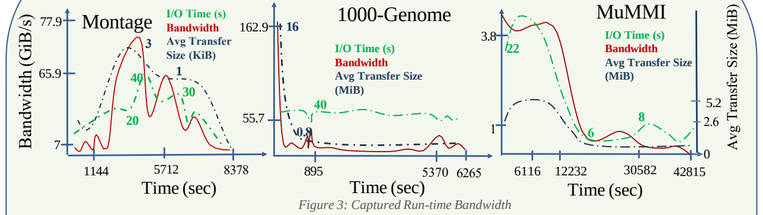
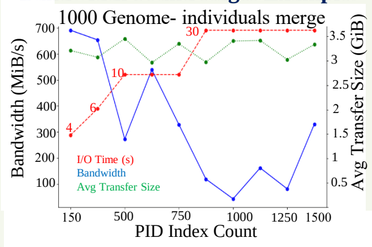


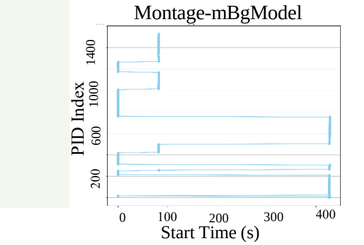
Figure 3: Captured Run-time Bandwidth

Bandwidth bound stages Example:



Cumulative bandwidth after progressively adding application instances plateaus.

Resource bound stages Example:



The Starting time of different PID indexes varies due to limited resources.

Figure 4: I/O bound stages limited by the Parallel File System parallelism or the resources

Findings

Montage:

- ❑ *mFitExec:* bandwidth-bound, Suggestion: data aggregation in the PFS itself.
- ❑ *mBgModel:* resource-bound, Suggestion: Dynamic Scheduling with Flux.

1000 Genome:

- ❑ *mutations overlap, merge individuals:* bandwidth-bound, Suggestion: use of isolated storage solutions such as node-local storage
- ❑ *individuals:* resource-bound , can be benefitted from Dynamic Scheduling.

MuMMI:

- ❑ It is not I/O bound
- ❑ Uses optimizations such as Flux hierarchical scheduling to isolate simulation-analysis pairs and shared memory usage.

I/O Characterization Results

Montage: mAdd (4.4%I/O) >> mImgtbl (3.22%I/O) >> mFitExec (2.2%I/O) >> mBgModel (1.5%I/O) >> others (<1%I/O)
1000 Genome: individuals merge (47%I/O) >> mutations overlap (45%I/O) >> frequency (43%I/O) >> individuals (9.9%I/O) >> sifting (1%I/O)
MuMMI: cganalysis (0.9%I/O) >> create_sims (<0.5%I/O)

Workflow	I/O thread	Application processes	Read size			I/O bound stage	Non I/O bound stage
			Max	Avg	Min		
Montage	42186	1534	1 MB	20 B	1 B	mFitExec	mBgExec
1000 Genome	2644	1534	16 MB	2 MB	5 KB	mutations overlap	sifting
MuMMI	22949	1408	588 MB	11 MB	6 KB	cganalysis	create_sims

Table V: Software, Hardware and Experimental Set-Up

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