I/O Characterization and Performance Evaluation of BeeGFS for Deep Learning

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8/12/19

48th International Conference on Parallel Processing (ICPP 2019), Kyoto, Japan

Outline

- Overview
- BeeGFS Introduction
- Deep Learning I/O Pattern
- Experimental Results and Key Observations
- Conclusion and Future Works

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- **Overview**
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Motivations

- BeeGFS is an emerging Parallel File System (PFS) that is interesting for a systematic performance analysis
- Deep Learning (DL) applications are very common HPC workloads on modern supercomputers
- Most of the time DL applications read files of a dataset kept on PFS during training phase
- **Our research aims at evaluating BeeGFS focusing on DL application workloads on HPC systems**

Key Contributions

- Identify the I/O patterns posed by DL applications
- Evaluate the impact of read/write on BeeGFS
- Analyze metadata performance of BeeGFS
- Evaluate BeeGFS using DL application benchmarks

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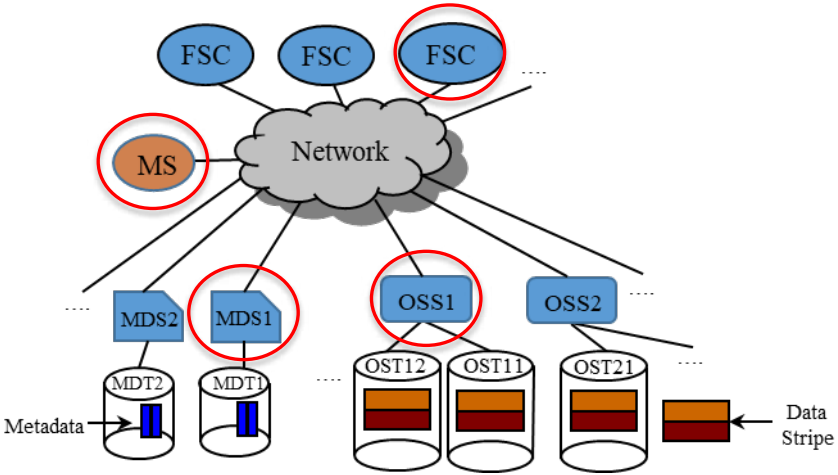
BeeGFS Software Architecture

- Management Server (MS)
  - Tracks initial connectivity information
- Metadata Server (MDS)
  - One Metadata Target per MDS
  - Maintains exclusive part of namespace
- Object Storage Server (OSS)
  - One or multiple Object Storage Targets (OST)
  - OST is generally RAID-set with POSIX compliant file system
- File System Client (FSC)
  - Kernel module to expose functions



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Deep Learning Frameworks

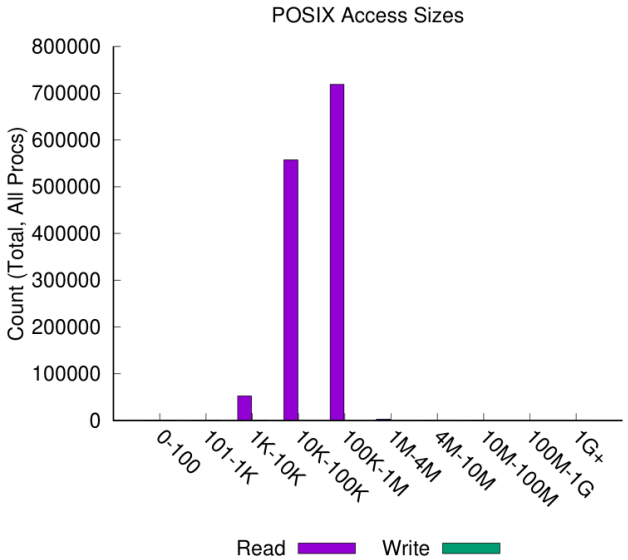
- Livermore Big Artificial Neural Network Toolkit (LBANN)
  - A neural network toolkit for HPC developed at LLNL
  - **Dataset specific specialized input pipeline**
- TensorFlow (TF) and Horovod
  - TF is a machine learning development platform by Google
  - Horovod helps enable HPC features in TF, Torch, etc.
  - **TF provides Dataset API for importing data while training**

Deep Learning Applications and Datasets

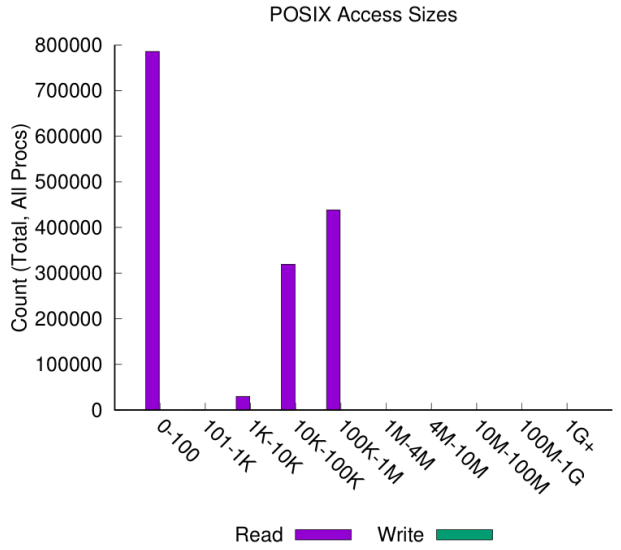
- AlexNet
  - 8 layer Convolutional Neural Network (CNN) for Image Recognition
- ResNet50
  - 50 layer Deep Residual Network for Image Classification
- ImageNet
  - Huge labelled image dataset with ~1.2 million images
  - Average file size is ~100 K

Deep Learning I/O Challenges on PFS

LBANN ImageNet Reader



TF Dataset API Input Pipeline



- Small I/O accesses for both LBANN and TF reported by Darshan-3.1.7
- Less data is read compared to huge metadata overhead
- No PFS caching due to randomization at each epoch

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System Configuration

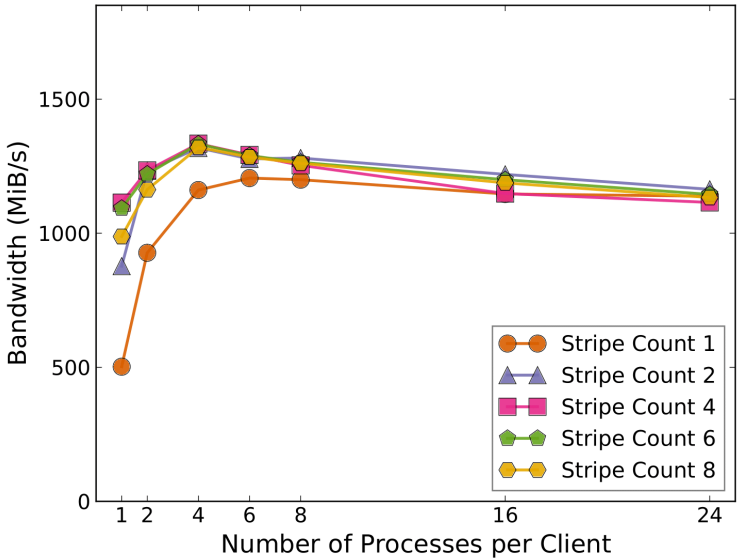
- All the experiments performed on **Catalyst** at LLNL
- **BeeGFS setup**
  - 338 TB BeeGFS-7.1.2 installation on Catalyst
  - 12 server hosts with QLogic Infiniband QDR interconnect
  - 12 OSS each with 2 OSTs
    - 1 OST: 4 HDD with ZFS RAID-Z and ZFS intent log on SSD
    - Level 2 Adjustable Replacement Cache on DRAM
  - 36 MDS each with 1 MDT
    - 3 MDS running per server host
    - 1 MDT: 4 SSD with ZFS RAID-Z formatting

Benchmarking Tools

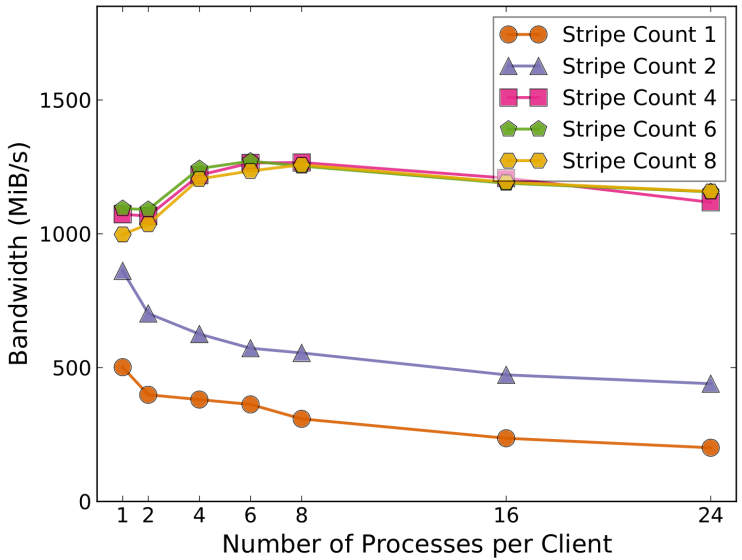
- Interleaved-Or-Random (IOR) version 2.10.3
  - File-per-process (N-N) and Single-shared-file (N-1) read/write with 240 GiB total file size
- MDTest-1.9.3
  - File create, stat and read operations
  - Shared-file, flat directory and single-depth hierarchical directory
- Deep Learning Benchmarks
  - AlexNet and ResNet-50 over ImageNet on LBANN
  - ImageNet reader pipeline on TF Dataset API and Horovod

Single Client Read Performance

File-per-process (N-N)



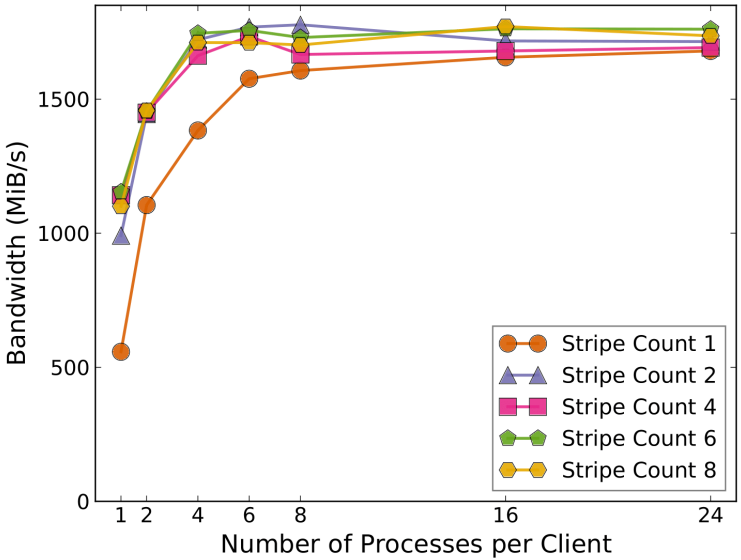
Single-shared-file (N-1)



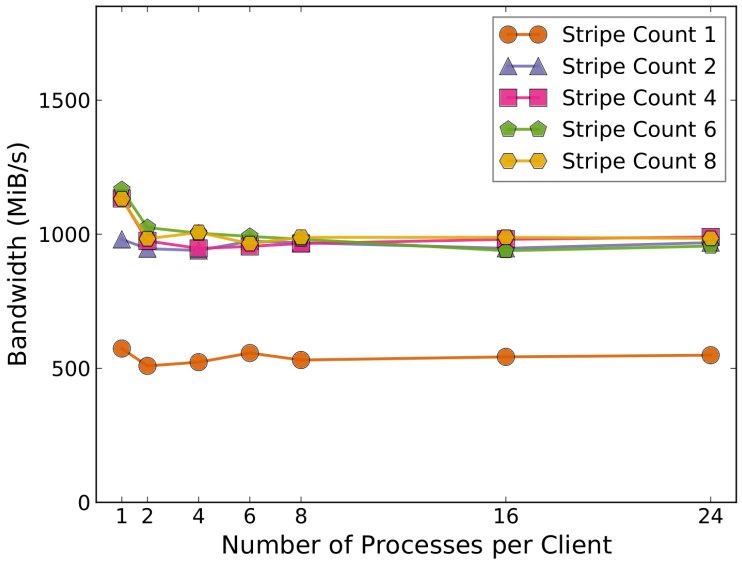
- N-N Read bandwidth reaches saturation point for network bandwidth
- N-1 Read bandwidth behaves differently for stripe count lower than 4

Single Client Write Performance

File-per-process (N-N)



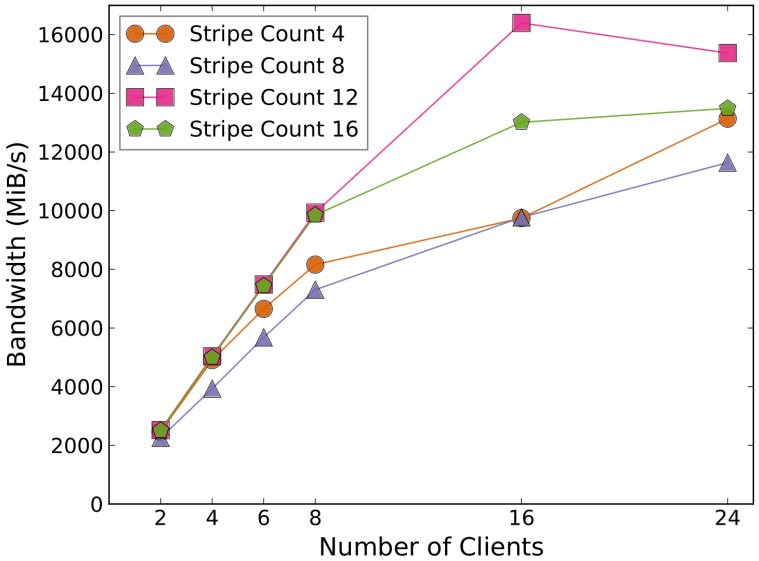
Single-shared-file (N-1)



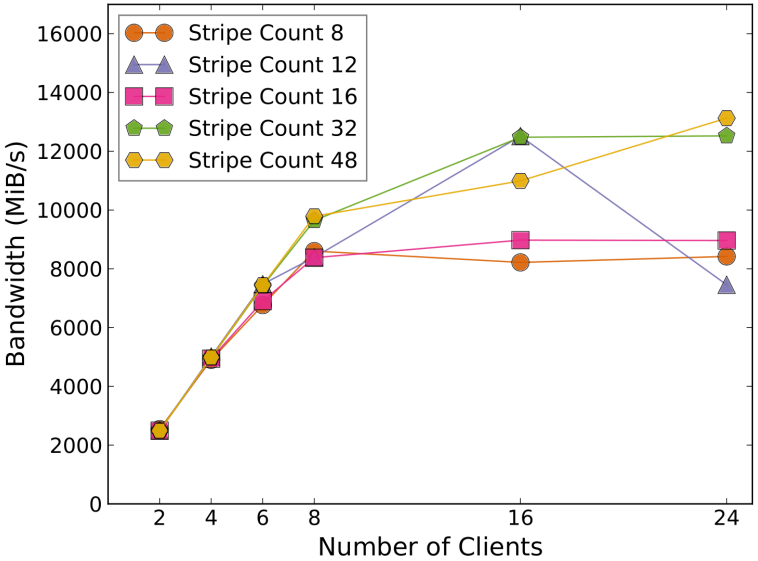
- N-N write bandwidth increases with process count and saturates
- N-1 write bandwidth does not scale as good as N-N write

Scale-out Read Performance

File-per-process (N-N)



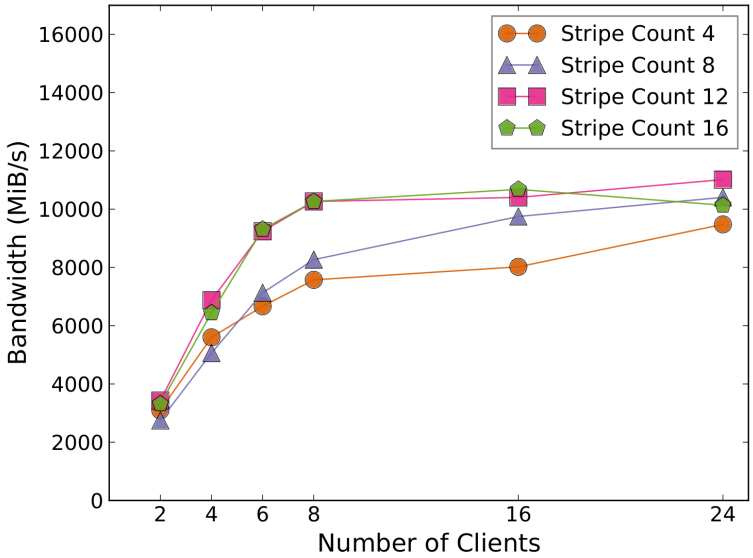
Single-shared-file (N-1)



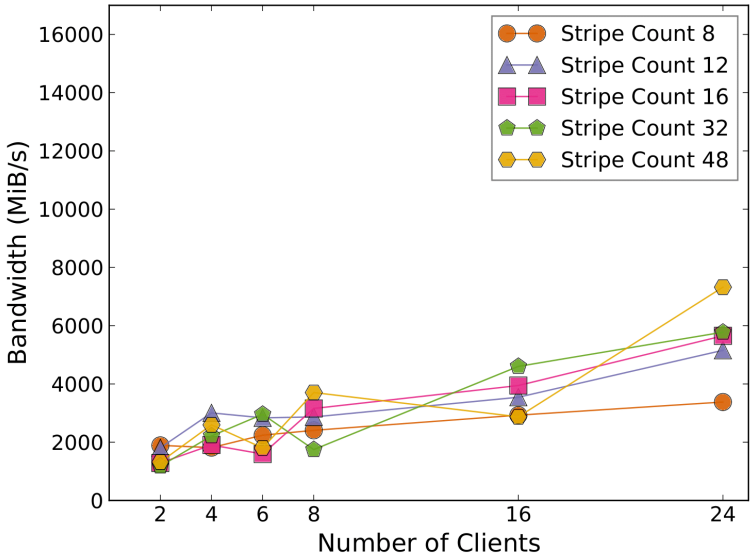
- N-N read bandwidth scales smoothly with increasing number of clients
- Bandwidth of N-1 read is slightly lower that of N-N read

Scale-out Write Performance

File-per-process

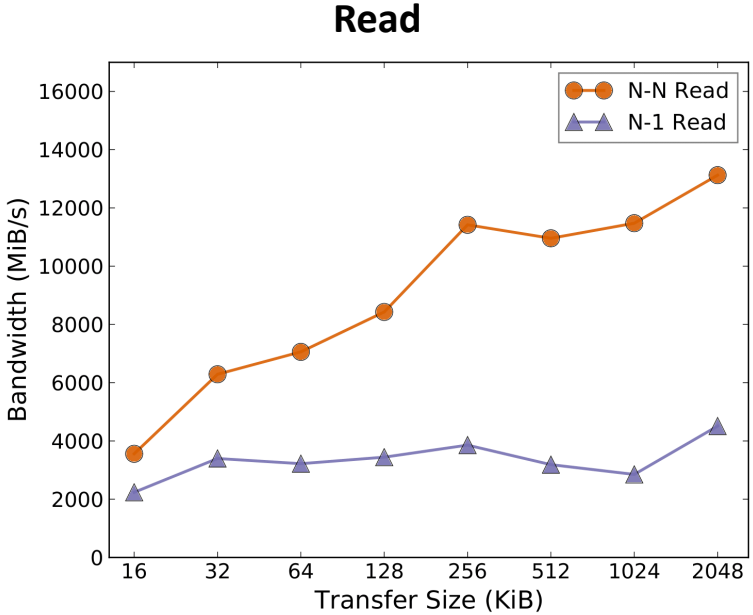


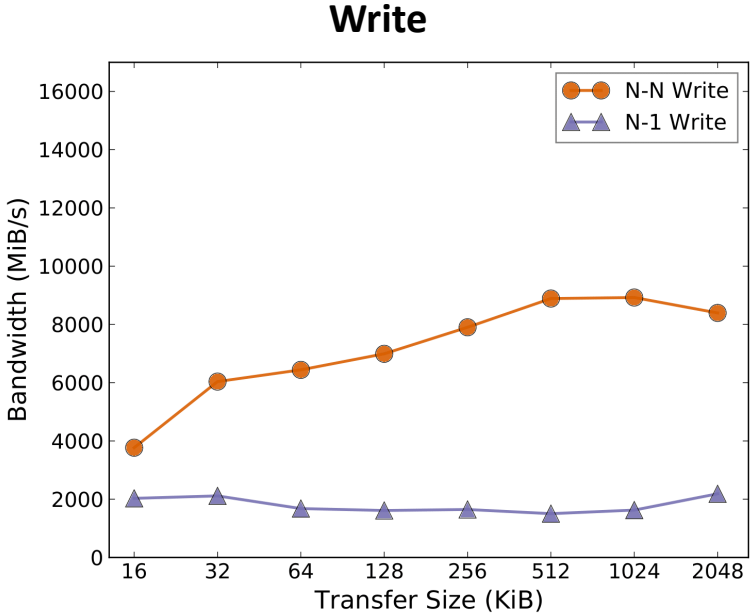
Single-shared-file



- N-N write bandwidth shows good scalability
- N-1 write bandwidth is almost half of N-N write bandwidth

Multi Client Varying Transfer Sizes



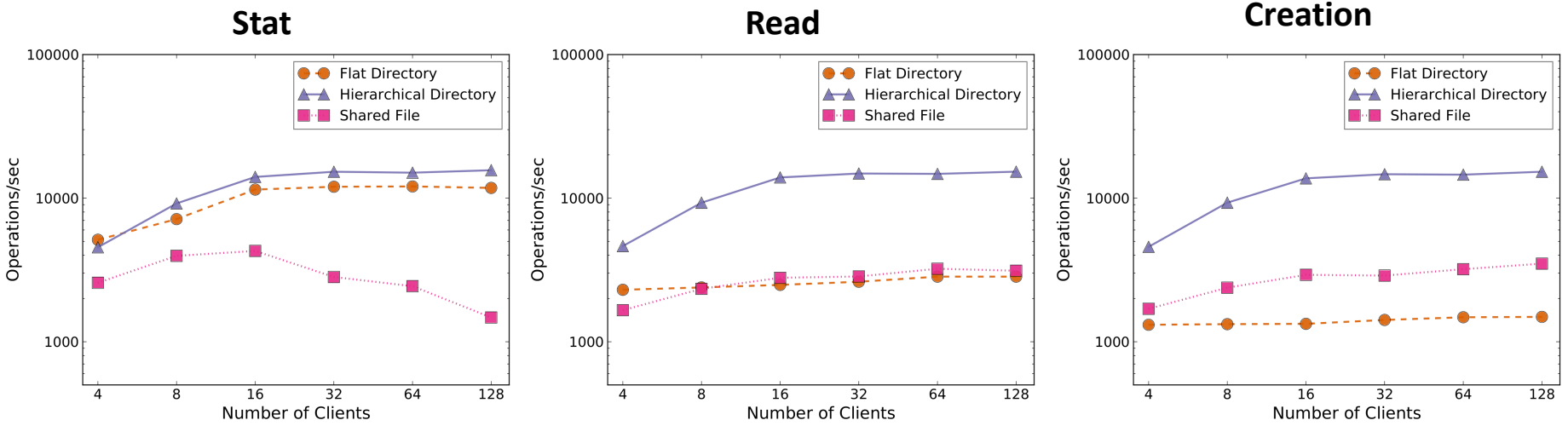


- Vary the transfer size for 16 clients and 8 processes per client
- N-N workloads handled better with increasing transfer size
- N-N bandwidths are better than N-1 as usual

I/O Observations

- N-N workload is almost always better than N-1
  - N-N read workload is closer to actual DL training I/O
  - Checkpointing and logging should avoid N-1 write
- Increasing stripe count is not always necessary
  - Need to balance resource utilization and performance
  - Lower striping leaves more devices available with reasonable performance

Multi Client Metadata Performance



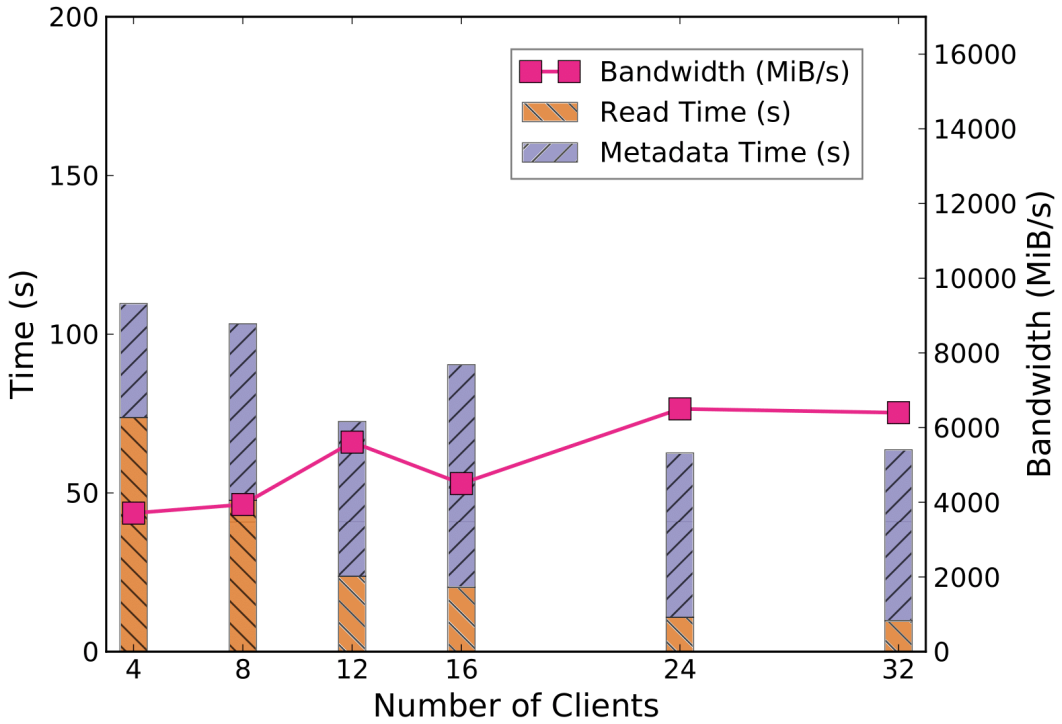
- File stat performance is good for both flat and hierarchical directory structures
- Single-depth hierarchical directory structure is the best for file open and close
- File creation metadata operation can leverage hierarchical directory structure

Metadata Observations

- Hierarchical file organization is beneficial to metadata management in BeeGFS
  - Dataset files should be arranged in hierarchical directories
  - ImageNet files are arranged in single-depth subdirectories

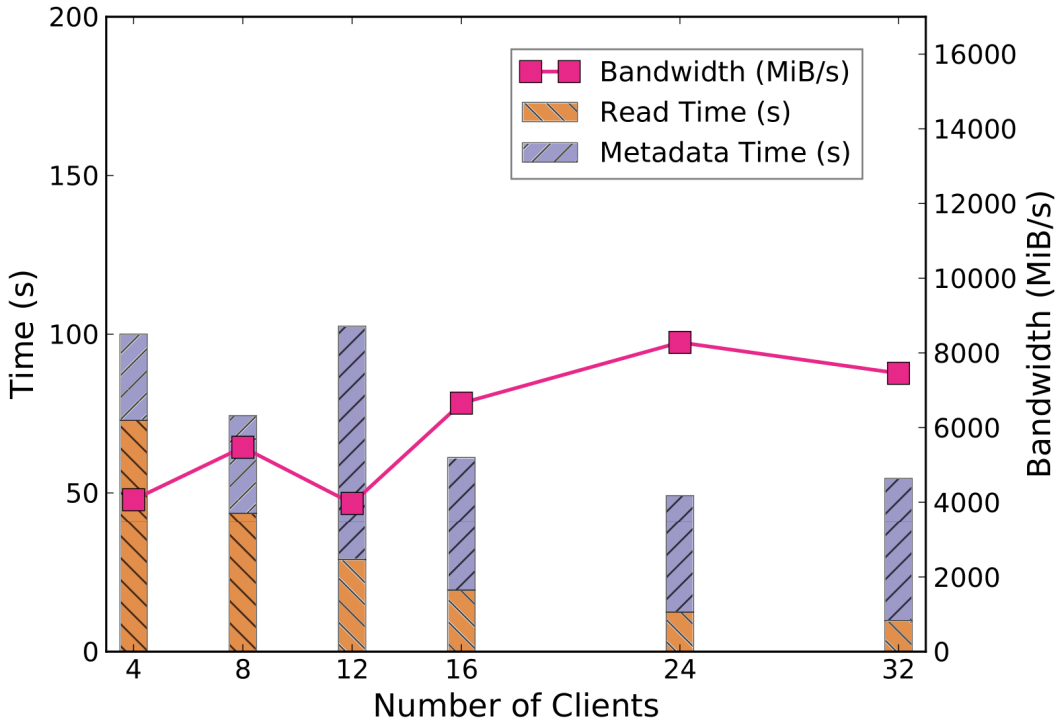
AlexNet over ImageNet on LBANN

- Read time decreases with increasing nodes
- Read bandwidth does not scale much
- Metadata overhead governs the overall throughput



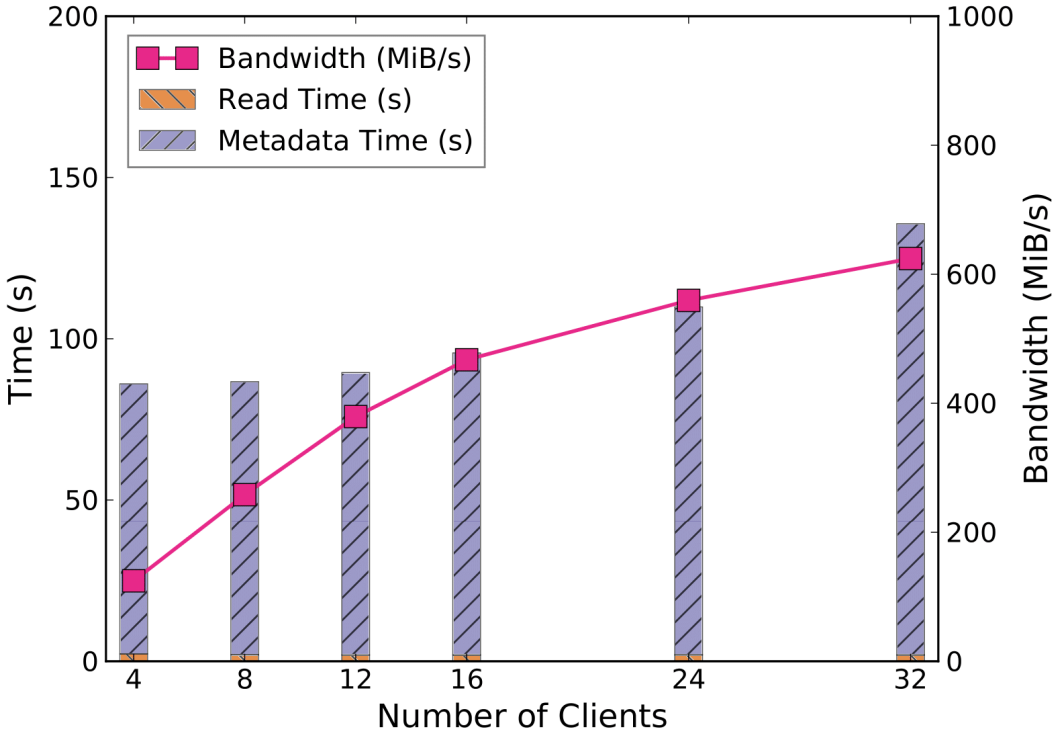
ResNet50 over ImageNet on LBANN

- AlexNet and ResNet50 both uses the same pipeline
- ImageNet dataset specific input pipeline in LBANN
- Similar trends for read throughput



ImageNet Data Reader on TF Dataset API

- Initial level tests on distributed TensorFlow
- Less data read compared to LBANN and bandwidth is low
- Metadata is a notable bottleneck



DL Application Benchmark Observations

- BeeGFS can reasonably handle LBANN DL I/O pattern
  - Read time lessens with more clients
  - Metadata overhead increases less steeply
- The directory structure of ImageNet is helpful for BeeGFS
  - Single-depth hierarchical directory structure in ImageNet assists metadata manager
- TF offers internal optimizations for file reading
  - tf.read_file through python wrapper invokes tiny file reads
- Metadata handling is a notable bottleneck in both LBANN and TF

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Conclusion and Future Works

- We perform microscopic data and metadata I/O performance evaluation of BeeGFS
- We discuss all the results and observations in the context of Deep Learning I/O patterns on BeeGFS
- We plan to perform more in-depth analysis on I/O workload by applications built atop TensorFlow
- We want to compile characterization data on more BeeGFS features, e.g., Storage Pool, BeeOND, etc.

Sponsors

This work is performed under the auspices of the U.S. Depart- ment of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344. LLNL-PRES-784219. This work is also supported in part by the National Science Foundation awards 1561041, 1564647, 1744336, 1763547, and 1822737.

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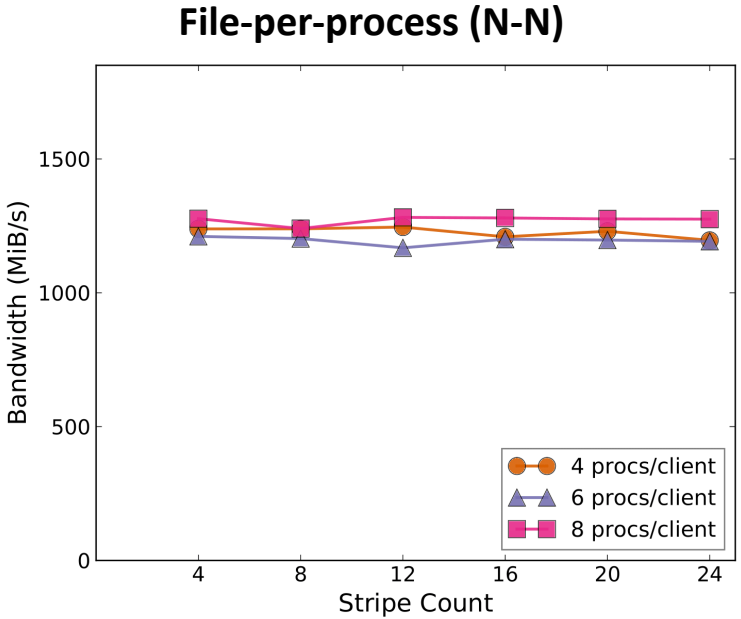
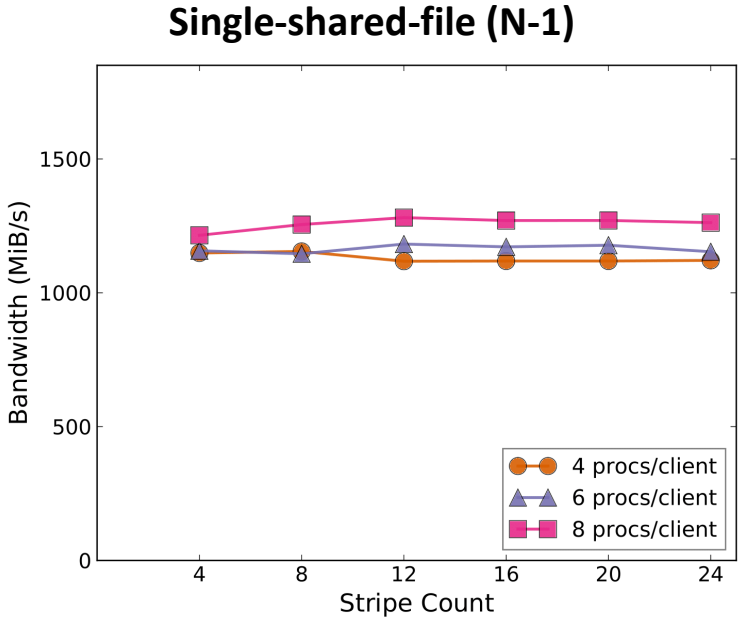
Thank you

Questions?

Backup

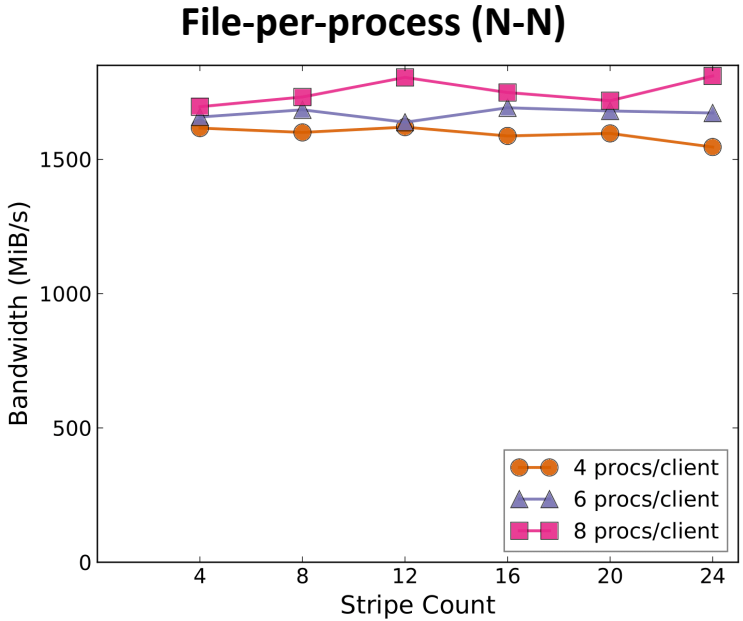
Single Client Read Performance (Contd.)

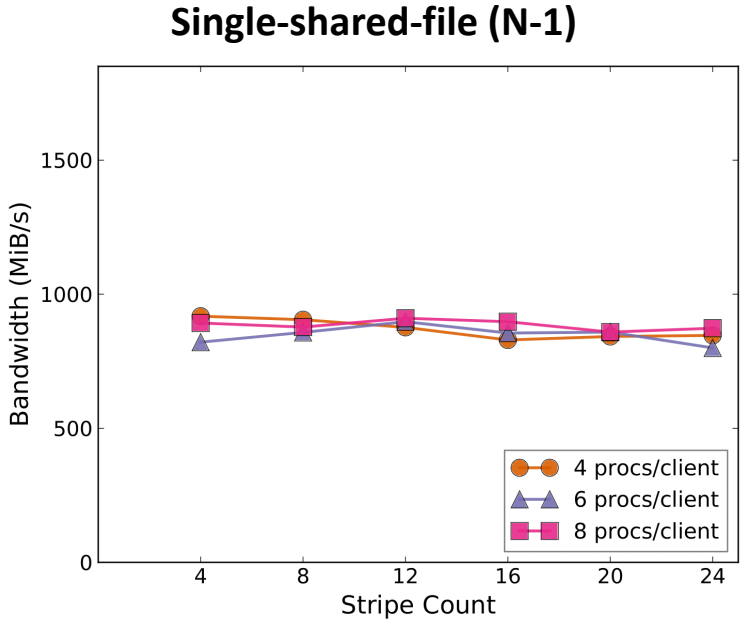




- N-N and N-1 read behave similarly with increasing stripes
- Lower stripe count ensures cost-efficient resource utilization

Single Client Write Performance (Contd.)





- N-N and N-1 write bandwidth both do not change much with stripe count
- Lower stripe count ensures more available storage devices