

Institute for Computer Science



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Influence of the file system on the performance of machine learning workloads

Project set up and preliminary results

Preliminary results



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Input/Output bottleneck is a problem for machine learning

- ML gaining more and more importance
 - Better and more efficient algorithms
 - Increasingly large datasets for training
- I/O takes up 90% of total training time
 - Costs resources such as time and money
 - Environmentally unsustainable



Figure: Examples of popular machine learning models

Pumma et al., "Scalable Deep Learning via I/O Analysis and Optimization" Jumper et al., "Highly accurate protein structure prediction with AlphaFold" https://chat.openai.com/ https://stablediffusionweb.com/

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Storage file systems

- Distribution across multiple servers
- I/O parallelism
- Redundancy for host failure security
- Scalability of performance and capacity
- Separation of functionality
 - Object Data Storage (ODS)
 - Metadata Server (MDS)
 - Access Server

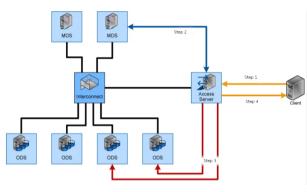


Figure: Exemplary storage file system architecture

https://www.itwm.fraunhofer.de/en/departments/hpc/fraunhofer-parallel-file-system-beegfs.html https://www.comconsult.com/hochleistungs-dateisysteme/

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Appendix

Lustre

- Open source parallel file system
- By researchers of Carnegie Mellon University of the US
- NHR@Göttingen: Lustre at GWDG
 - Emmy: CPU Cluster
 - Grete: GPU Cluster





Figure: Supercomputer Emmy tile

https://www.lustre.org/about/ https://gwdg.de/hpc/systems/emmy/ https://info.gwdg.de/news/how-to-use-our-new-gpu-cluster-grete-for-hlrn-users/ https://gwdg.de/hpc/systems/

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BeeGFS

- Shared source parallel file system
- By Frauenhofer Institute
- BeeGFS at GWDG
 - Scientific Compute Cluster (SCC): CPU & GPU Cluster



Figure: Supercomputer SCC tile



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Dataset: Conceptual Captions

- ~3.3M image-caption pairs
- Harvested from web by Google Al
- Competition: image captioning task
- Project subset
 - 12 720 images
 - ▶ Size: ~8GB



Figure: Google Al Conceptual Captions dataset logo

https://ai.google.com/research/ConceptualCaptions/ https://huggingface.co/datasets/conceptual_captions

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HuggingFace provides

- In general
 - A collaboration platform for ML community
 - Open-source ML libraries, datasets and models



https://huggingface.co/brand https://huggingface.co/datasets/conceptual_captions

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HuggingFace provides

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- For the conceptual captions dataset
 - Data including image_url, caption, labels and some other information
 - Code to load dataset and fetch the images
 - Note: save to scratch not home filesystem

```
from datasets import load_dataset
dset = load_dataset("conceptual_captions")
```

Emmy did not like HuggingFace

Provided download code produced...

▶ 76 lines of error traceback

File "/scratch/usr/nimestha/mambaforge/envs/scap_env/lib/ python3.12/site-packages/requests/adapters.py", line 507, in send raise ConnectTimeout(e, request=request) requests.exceptions.ConnectTimeout:

(MaxRetryError("HTTPSConnectionPool(host='huggingface.co', port=443): Max retries exceeded with url: /api/whoami-v2 (Caused by

ConnectTimeoutError (<urllib3.connection.HTTPSConnection object at 0x2aaaclc42ab0>, 'Connection to huggingface.co timed out. (connect timeout=None)'))"), '(Request ID: bb81d713-1a76-4b53-b323-62811a84ec7a)'

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Emmy did not like HuggingFace cont.

Workaround

- Use downloaded files on SCC
- Upload with scp command for file transfer

\$ scp directory_to_upload remote_username@glogin.hlrn.de:/remote/directory



Darshan

- Open source I/O characterisation tool
- Post mortem analysis
 - Elapsed time
 - Access sizes
 - Access pattern
 - File names for each file opened by an application



Figure: Darshan web logo

Kunkel et al., "Tools for analyzing parallel I/O" https://www.mcs.anl.gov/research/projects/darshan/

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Darshan installation

- \$ module load openmpi \$ wget https://ftp.mcs.anl.gov/pub/darshan/releases/darshan-3.4.4.tar.gz \$ tar -xvzf darshan-3.4.4.tar.gz \$ cd darshan-3.4.4/ \$./prepare \$ cd darshan-runtime/ \$./configure --with-log-path=/darshan-logs --with-jobid-env=SLURM_JOB_ID --prefix=/scratch/users/username/darshan/ CC=mpicc \$ make & make install \$ cd ../darshan-util/
- \$ configure --prefix=/scratch/users/username/darshan/
- \$ make $\pmb{\&}$ make install

https://www.mcs.anl.gov/research/projects/darshan/docs/darshan-runtime.html
https://www.mcs.anl.gov/research/projects/darshan/docs/darshan-util.html

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Darshan log file usage

Darshan-parser

- Included in darshan-util
- Creates complete, human-readable, text-format version of log files

https://www.mcs.anl.gov/research/projects/darshan/docs/darshan-util.html https://pypi.org/project/darshan/3.4.0.0/#description

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Darshan-job-summary.pl

- Also included in darshan-util
- Creates graphical summary of the I/O activity as PDF

https://www.mcs.anl.gov/research/projects/darshan/docs/darshan-util.html https://pypi.org/project/darshan/3.4.0.0/#description

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Darshan log file usage

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Darshan-job-summary.pl

- Also included in darshan-util
- Creates graphical summary of the I/O activity as PDF

PyDarshan

- Python utilities to interact with Darshan log files
- Requires darshan-util
- Install via pip

```
$ pip install darshan==3.4.0.0
```

https://www.mcs.anl.gov/research/projects/darshan/docs/darshan-util.html https://pypi.org/project/darshan/3.4.0.0/#description

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Darshan log file usage: PyDarshan code example

pydarshan_ex.py

import darshan

Open darshan log
report = darshan.DarshanReport('example.darshan', read_all=False)

```
# Load some report data
report.mod_read_all_records('MPI-I0')
# or fetch all
report.read_all_generic_records()
```

Generate summaries for currently loaded data
Note: aggregations are still experimental and have to be activated:
darshan.enable_experimental()
report.summarize()

https://pypi.org/project/darshan/3.4.0.0/#description

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Define jobs for slurm via batch script

run.sbatch

#! /bin/bash

```
#SBATCH --mem 32G
#SBATCH -p medium
#SBATCH -t 01:00:00
```

export LD_PRELOAD=/scratch/users/username/darshan/lib/libdarshan.so

source /usr/users/username/.bashrc
source activate scap_env

module load openmpi

```
srun python test_run.py
```

How to choose partition

Description of available partitions

SCC: https://gwdg.de/en/hpc/systems/scc/

Name	Number of nodes	CPU & GPU	Number of CPU-Cores	Memory [GB]	Partition
amp	95	(i) 2 x Xeon Platinum 9242	48	384	[medium]

Emmy: https://www.hlrn.de/doc/display/PUB/Compute+node+partitions

Partition (number holds cores per node)	Node name	Max. walitime	Nodes	Max. nodes per job	Max. jobs per user	Usable memory MB per node	CPU, GPU type	Shared	<u>NPL</u> per node hour	Remark
standard96	gcn#	12:00:00	996	256	unlimited	362 000	Cascade 9242	×	96	default partition

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Some exploratory tests

I/O type	SCC	Emmy		
Reading	527.12 sec	945.18 sec		
Reading	pprox 8.79 min	pprox 15.75 min		
Writing	2425.50 sec	3611.15 sec		
whiting	pprox 40.43 min	pprox 60.19 min		

- Times averaged over 10 runs
- Used dataset
 - 12 720 images
 - ▶ ~8GB
- Used CPU partitions
 - SCC: medium (cascade lake)
 - Emmy: large40 (skylake)

Preliminary results

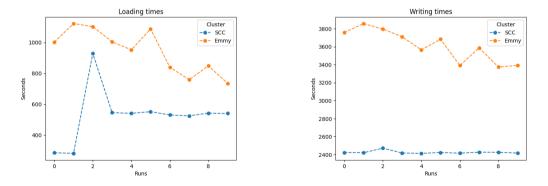
Stopping time is not sufficient

Standard deviation loading:

- ► SCC: 167.84 sec ≈ 2.80 min
- Emmy: 135.11 sec \approx 2.25 min

Standard deviation writing:

- ► SCC: 15.79 sec ≈ 0.26 min
- ▶ Emmy: 169.29 sec ≈ 2.82 min



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More runs mean more variation

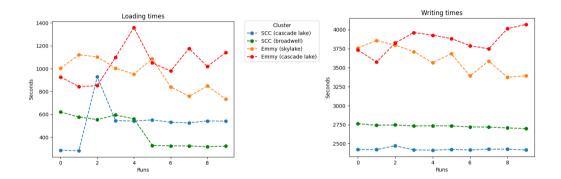


Table with avg. times and std in appendix

Preliminary results



Preliminary results using Darshan

"If anything can go wrong, it will."

- Captain Edward A. Murphy



https://www.phrases.org.uk/meanings/murphys-law.html https://medium.com/the-rookie-pm/on-murphys-law-agile-and-product-management-9158d3530a89

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Summary

Project set-up

- Parallel file systems: BeeGFS and Lustre
- Dataset: Conceptual Captions 3M
- Measurement tool: Darshan

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- Parallel file systems: BeeGFS and Lustre
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- Stopping time not sufficient
- Trend: Emmy slower than SCC

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- Parallel file systems: BeeGFS and Lustre
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Future work

- Get Darshan running
- Analyse log files for I/O performance

Preliminary results

- Stopping time not sufficient
- Trend: Emmy slower than SCC

References

- Jumper, John et al. "Highly accurate protein structure prediction with AlphaFold". In: *Nature* 596.7873 (2021), pp. 583–589.
- Kunkel, Julian Martin et al. "Tools for analyzing parallel I/O". In: High Performance Computing: ISC High Performance 2018 International Workshops, Frankfurt/Main, Germany, June 28, 2018, Revised Selected Papers 33. Springer. 2018, pp. 49–70.
- Pumma, Sarunya et al. "Scalable Deep Learning via I/O Analysis and Optimization". In: ACM Trans. Parallel Comput. 6.2 (July 2019). ISSN: 2329-4949. DOI: 10.1145/3331526. URL: https://doi.org/10.1145/3331526.

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Result overview

Cluster			SCC	Emmy		
Processor gen.		broadwell	cascade lake	skylake	cascade lake	
Reading	avg. times	7.53	8.79	15.75	17.41	
Reading	std	2.17	2.80	2.25	2.51	
Writing	avg. times	45.48	40.43	60.19	64.20	
	std	0.30	0.26	2.82	2.35	

Table: Times for loading and writing roughly 8GB of image data on different partitions of the SCC and Emmy averaged over 10 runs and the standard deviations of those runs. All times are given in minutes and rounded to two decimals.

Useful slurm commands

Submit batch script to start job

\$ sbatch run.sbatch

Review scheduled jobs

\$ squeue -u username JOBID PARTITION NAME USER STATE TIME NODES NODELIST(REASON) 5460973 medium run.sbatch username RUNNING 0:30 1 amp029

https://slurm.schedmd.com/documentation.html

Preliminary results

Useful slurm commands cont.

Cancel a job with JOBID

\$ scancel 5460973

Review available partitions and nodes

\$ sinfo
PARTITION AVAIL TIMELIMIT NODES STATE NODELIST
medium* up 2-00:00:00 1 idle amp025

https://slurm.schedmd.com/documentation.html