Deep Learning Optimized on Jean Zay

Dataset optimization

Storage spaces and data format

cnrs IDRIS

Dataset optimization

Main bottlenecks ◄

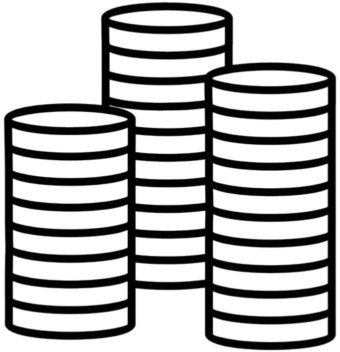
Data storage – various disk spaces ◄

Data format – at sample level ◄

Data format – at dataset level ◄

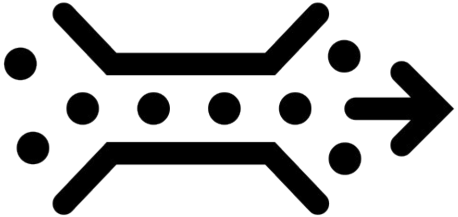
Bottlenecks upstream of DataLoader

Storage Disks



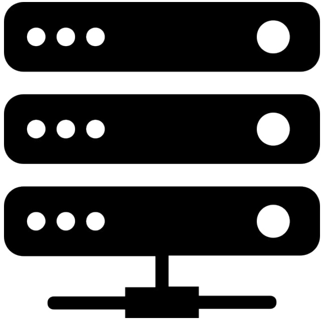
1. I/O performance

Interconnection Network
Omnipath



2. Shared Bandwidth

CPU workers



3. Decoder performance

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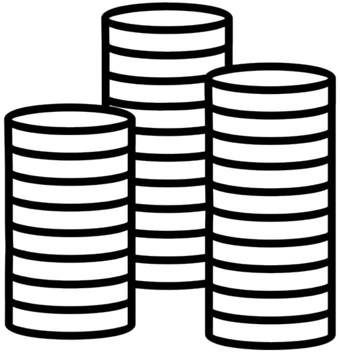

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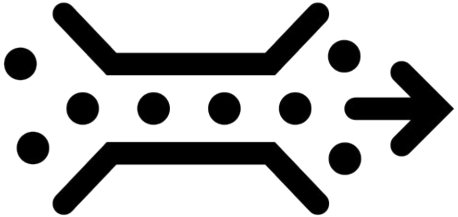

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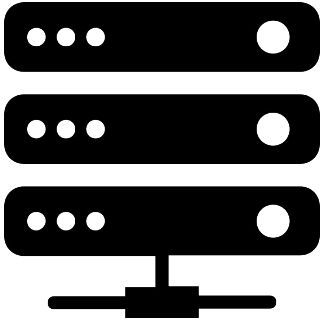
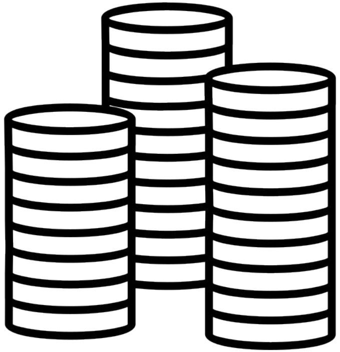


3. Decoder performance

Where should I store my dataset?

Various disk spaces

Storage Disks



1. I/O performance

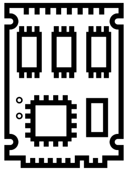
WORK / DSDIR

Rotative disk spaces

100 GB/s
OPA

SCRATCH

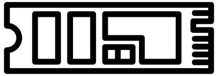
Full Flash



500 GB/s
OPA

NVMe

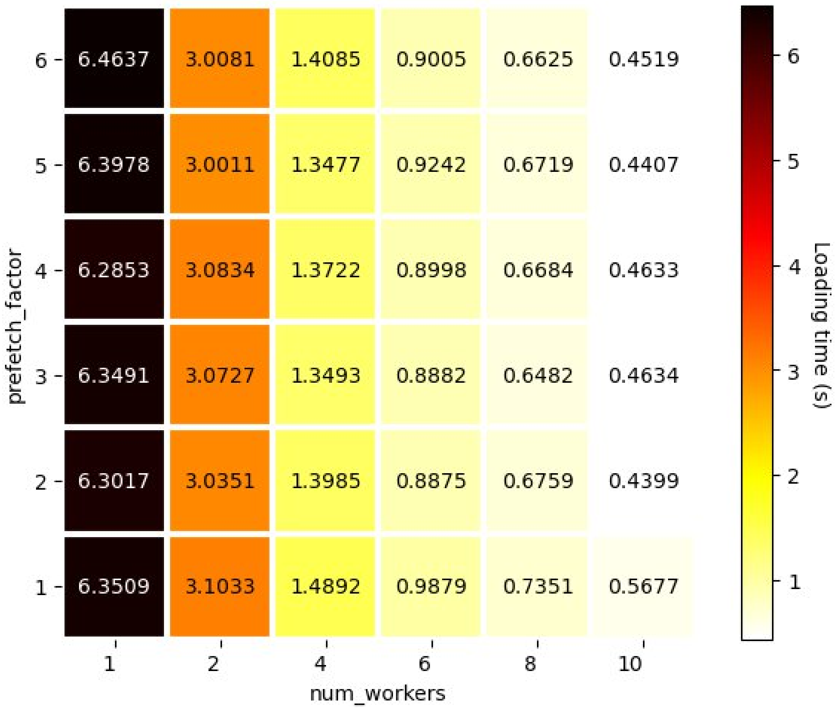
Local disk
(test configuration)

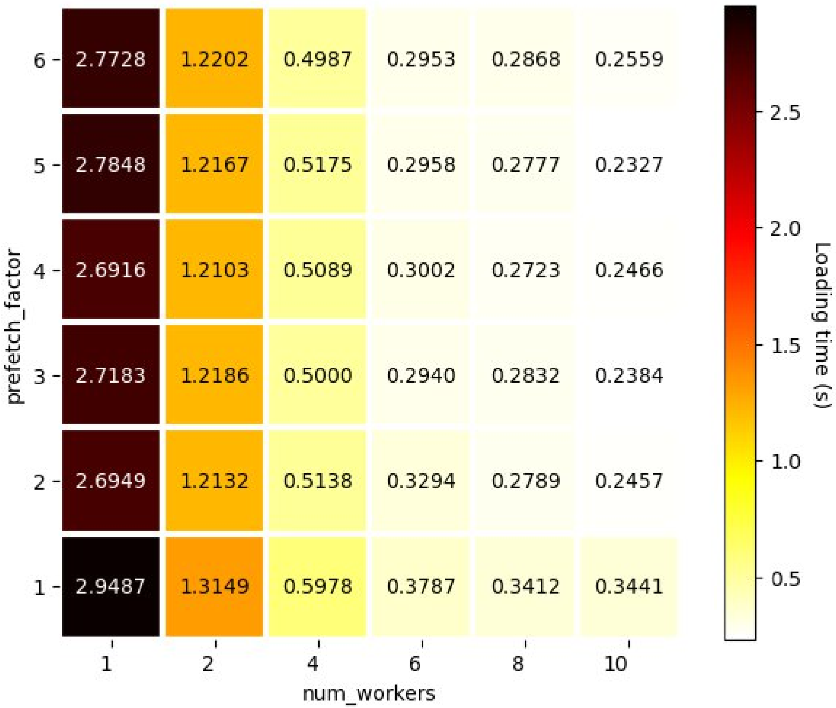


PCIe

Various disk spaces

dlojz.py - 50 iterations - test partition gpu_p4





WORK / DSDIR

100 GB/s - OPA

÷ 2

SCRATCH

500 GB/s - OPA

Various disk spaces

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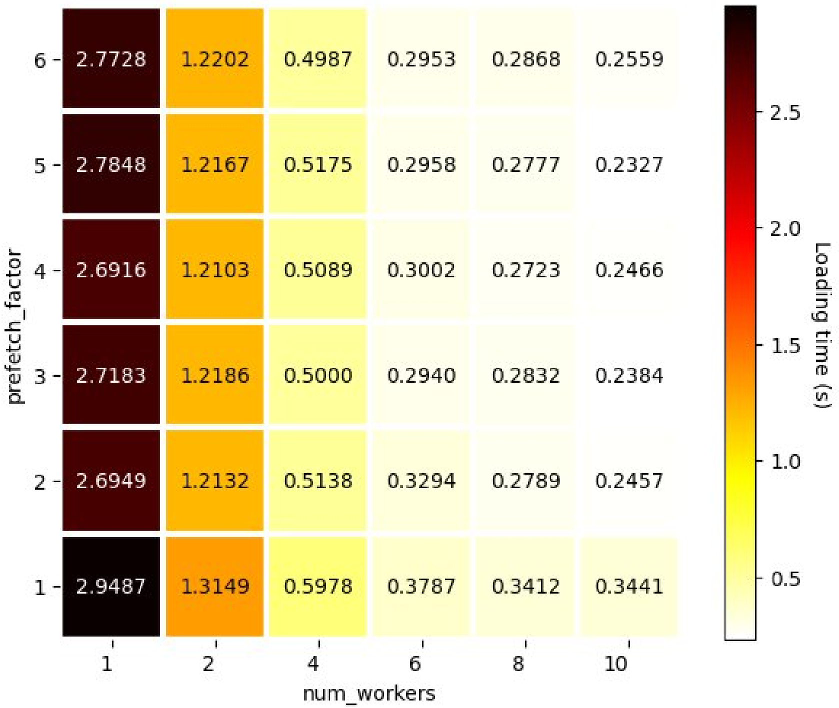

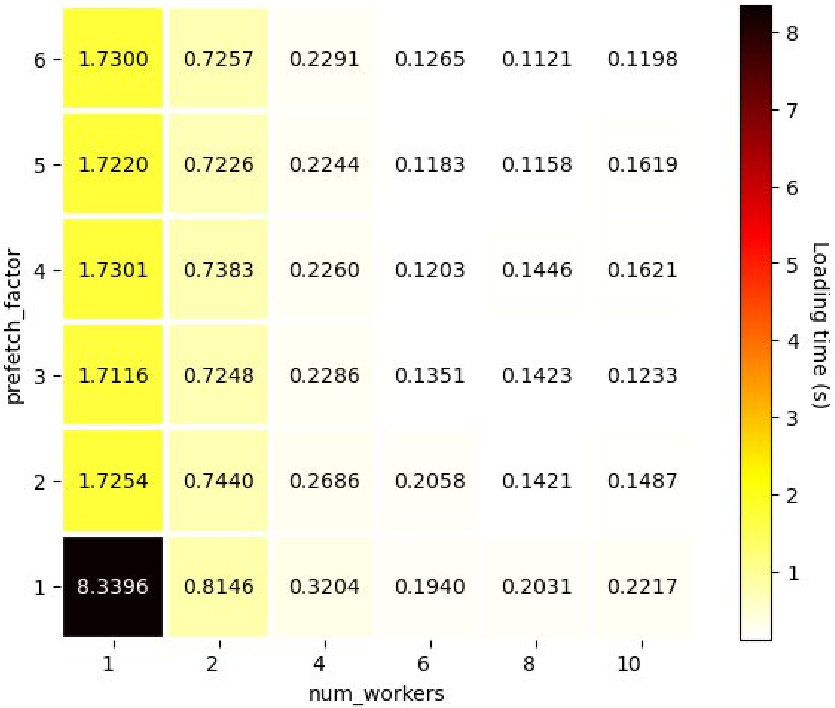

SCRATCH

500 GB/s - OPA

÷ 2

NVMe

PCIe

Various disk spaces

- **NVMe**
  - ✓ Best IO performance
  - – You need to copy your dataset on the local disk first, which can take a very long time
  - – This solution is not suitable at the scale of a supercomputer so it is not available to users
- **SCRATCH**
  - ✓ Second best IO performance
  - ✓ Very large quota (bytes and inodes)
  - – 30 days file lifespan
  - – Not backed up
- **WORK / DSDIR**
  - – Worst performance (but it is still acceptable)
  - – Only 5 TB and 500k inodes
  - ✓ IDRIS support team manages the dataset for you in the DSDIR (downloading, preprocessing,...)
  - ✓ Backed up

Dataset optimization

Main bottlenecks ◄

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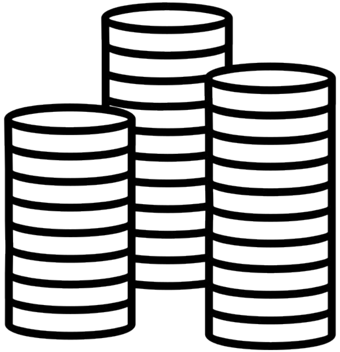
Data format – at sample level ◄

Data format – at dataset level ◄

Bottlenecks upstream of DataLoader

Storage Disks



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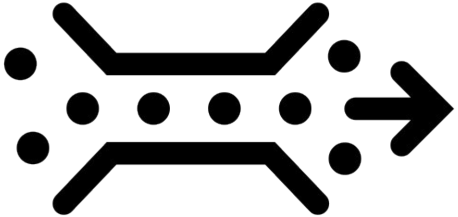
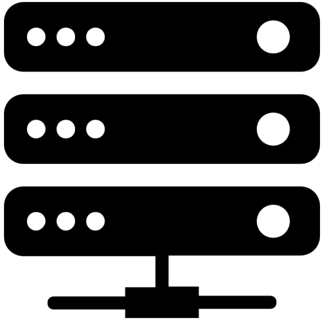


2. Shared Bandwidth

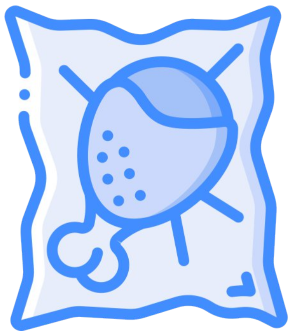
CPU workers



3. Decoder performance

Which format for my data?

At sample level - Sample decoding



Binary format: Pickle format, hdf5,...
Decoded more quickly, takes more space

- ✓ Decoder performance
- – Shared bandwidth
- – Storage volume

Compressed format: jpeg, png,...
Decoded more slowly, takes less space

- – Decoder performance
- ✓ Shared bandwidth
- ✓ Storage volume

Dataset optimisation

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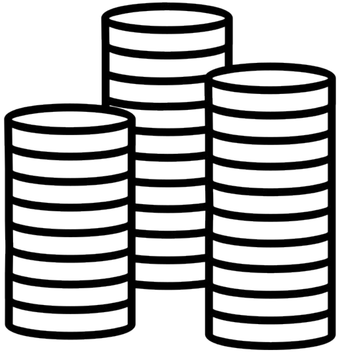
Data format – at sample level ◄

Data format – at dataset level ◄

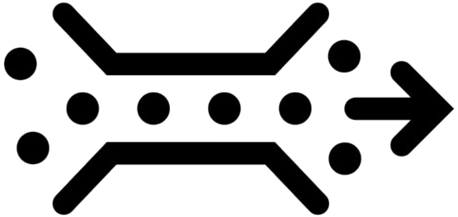
Bottlenecks upstream of DataLoader

Storage Disks



1. I/O performance

Interconnection Network
Omnipath



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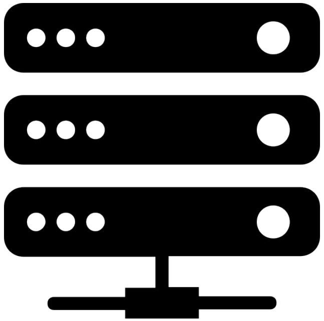
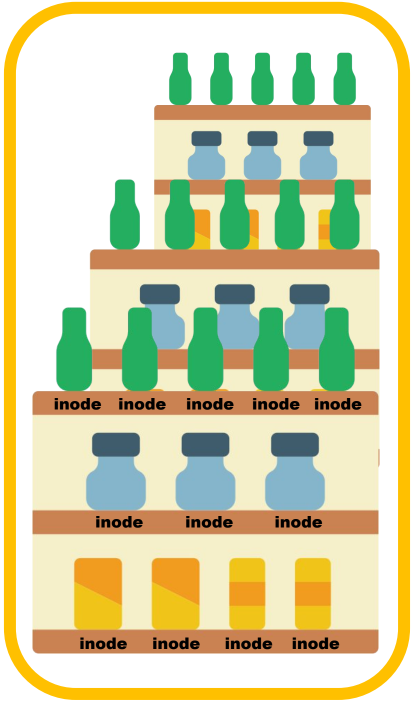


3. Decoder performance

Which format for my dataset?

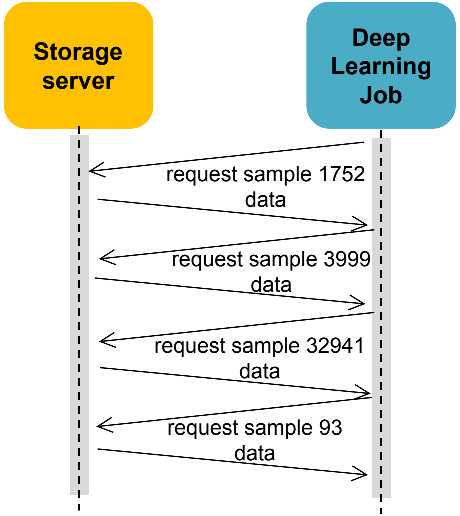
Intuitive way

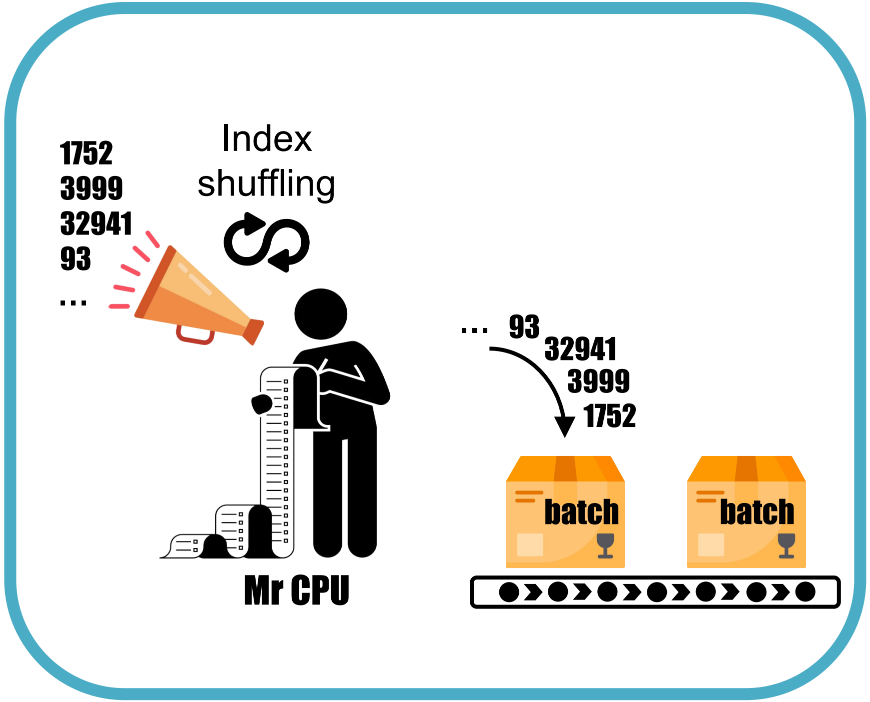


Map-style dataset

__getitem__

Random Access
to File Store





Pros: Easy to handle, random access possible

Cons: Lots of inodes, lots of I/Os

Too many inodes is an issue

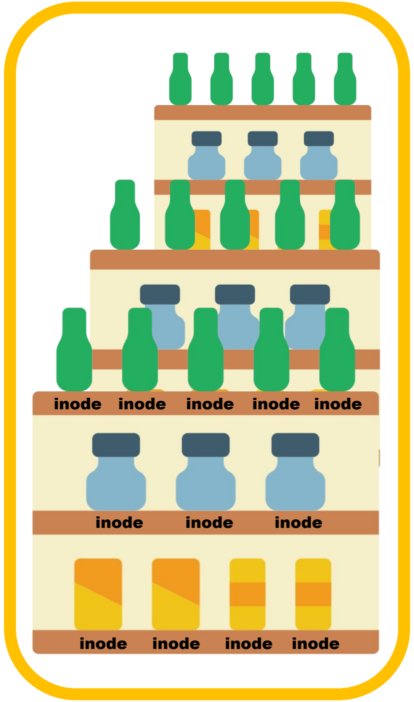
Error: Disk quota exceeded

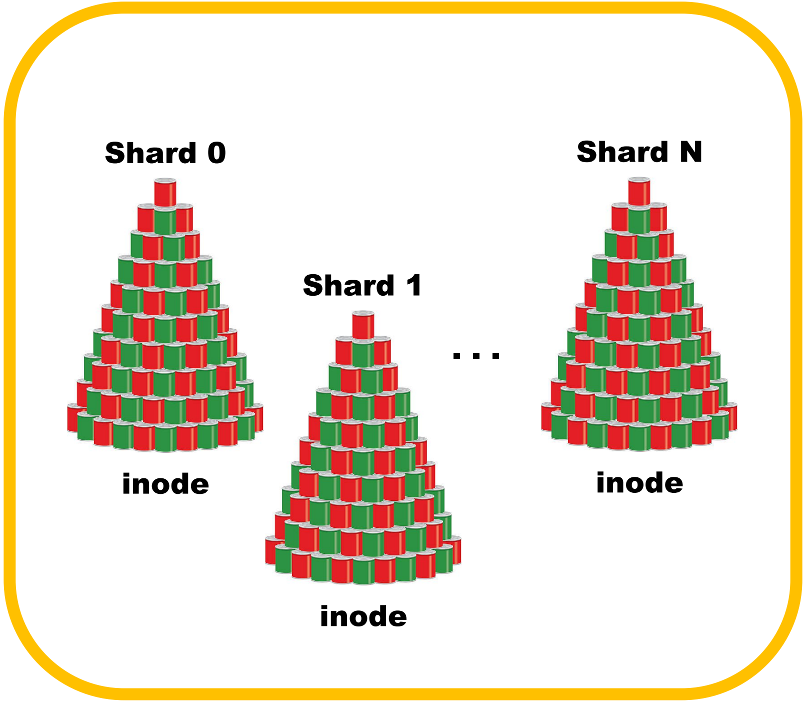
Reminder:

- $WORK quota per user is 5 TB / **500 kinodes**
- $SCRATCH safety quota per user is 250TB / **150 Minodes**

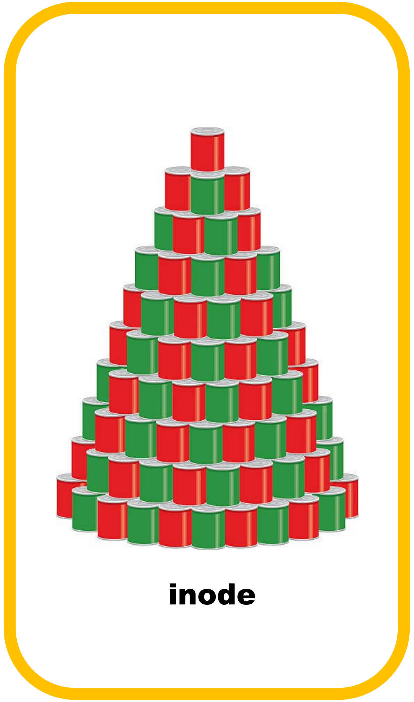
+ IBM Spectrum Scale file system does not like small file I/O intensive workloads

WebDataset format – Gathering inodes



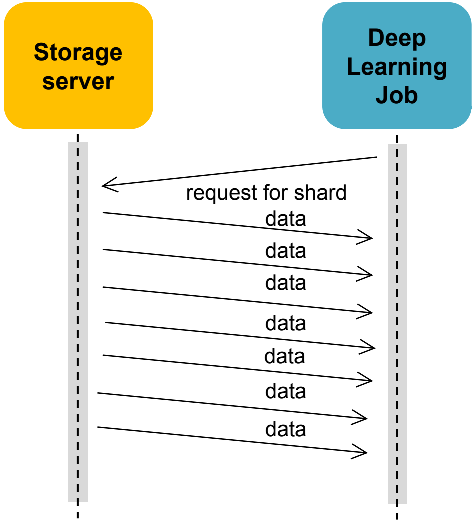


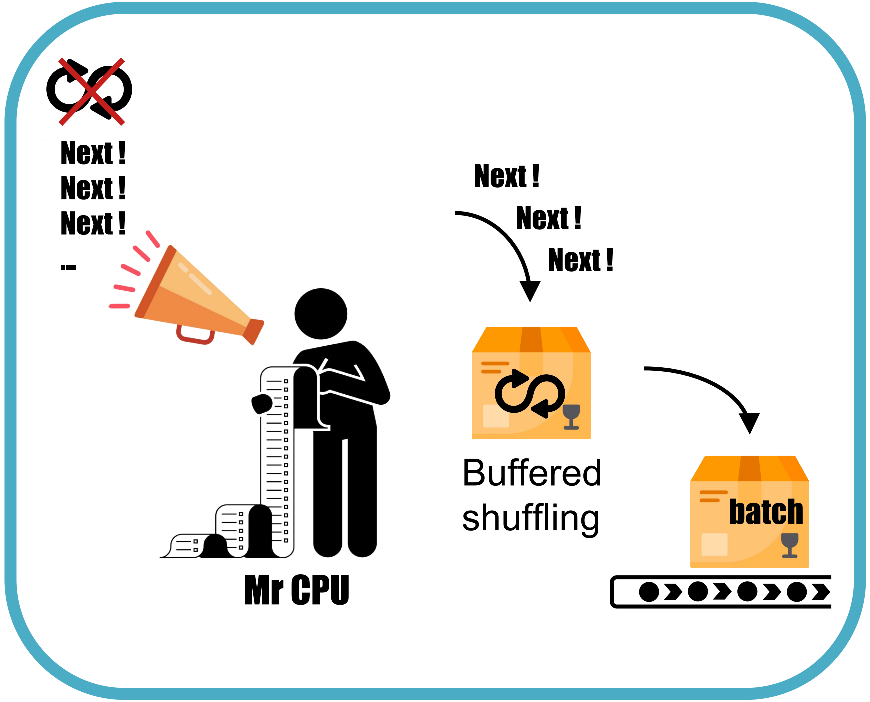
WebDataset format – Iterable dataset



Iterable-style dataset
__iter__

Pipelined Access
to Object Store

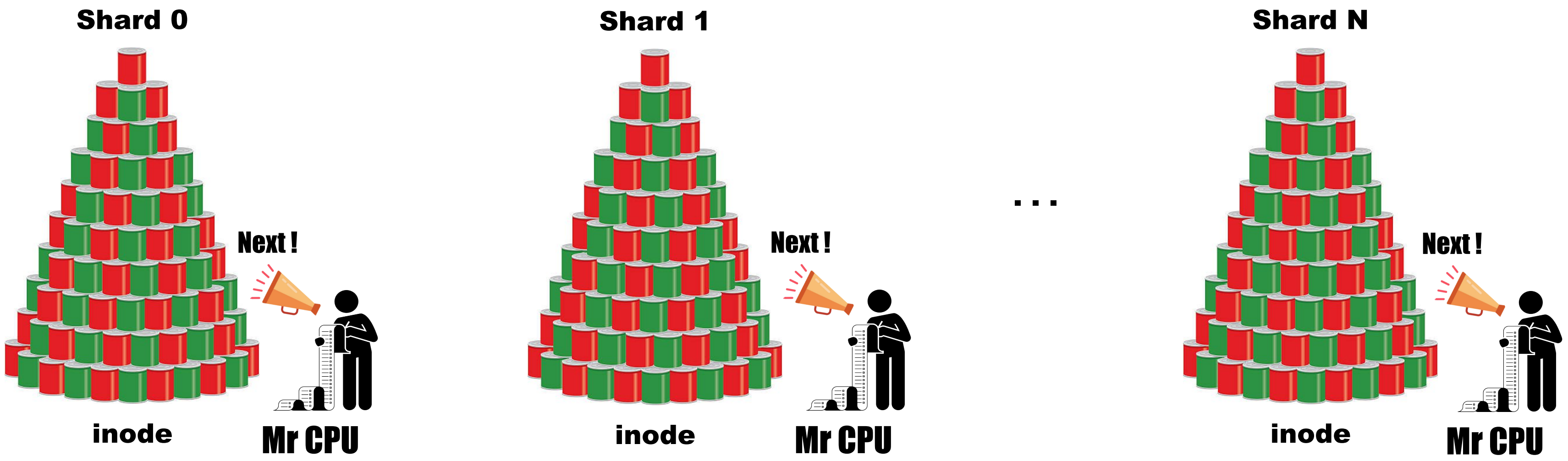




Pros: Fewer I/Os, fewer inodes
Cons: Difficult to shuffle or distribute, unknown dataset length

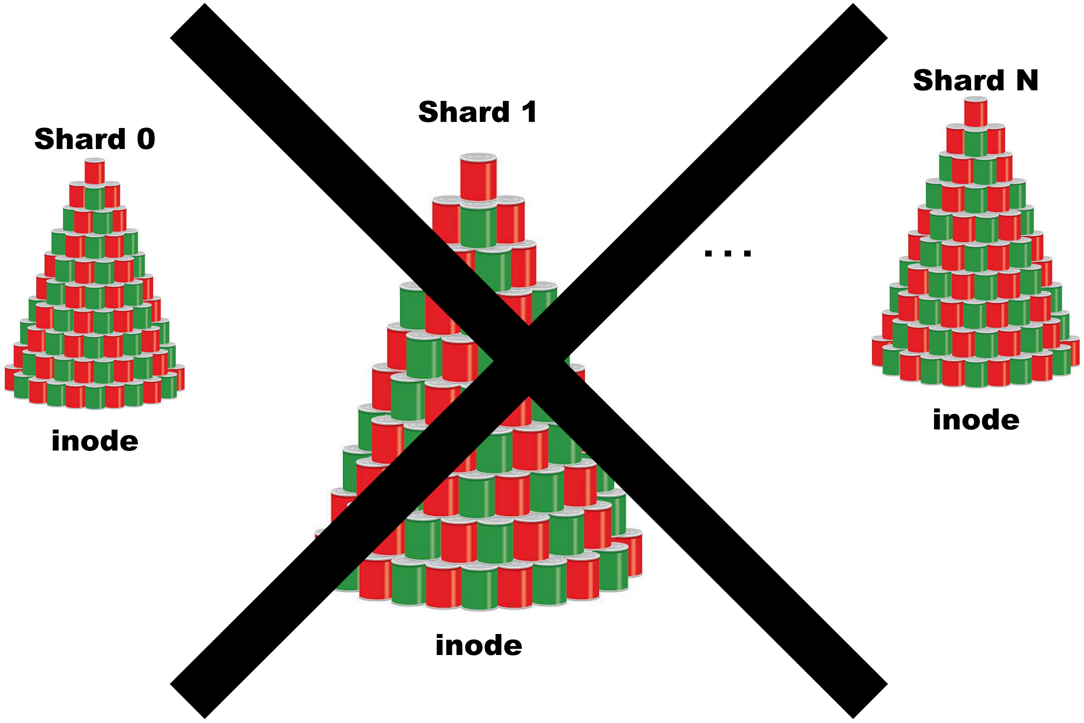
WebDataset format - Sharding

Sharding is necessary to benefit from parallel implementation
(DataLoader multi-processing and Distributed Data Parallelism).



The number of shards should be a multiple of the number of tasks/GPUs.

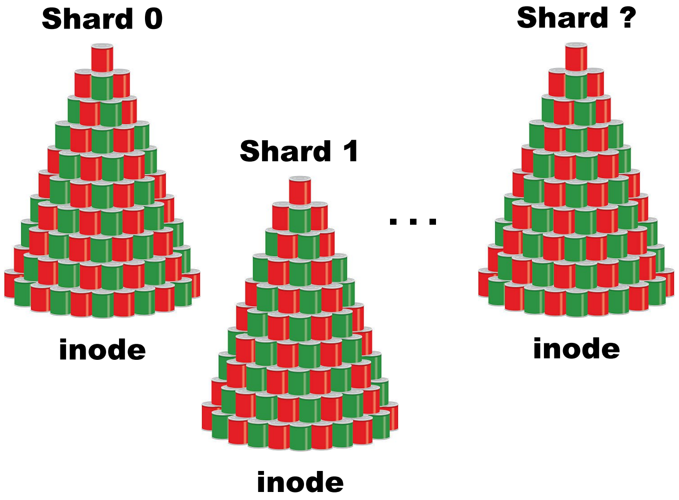
WebDataset format - Sharding



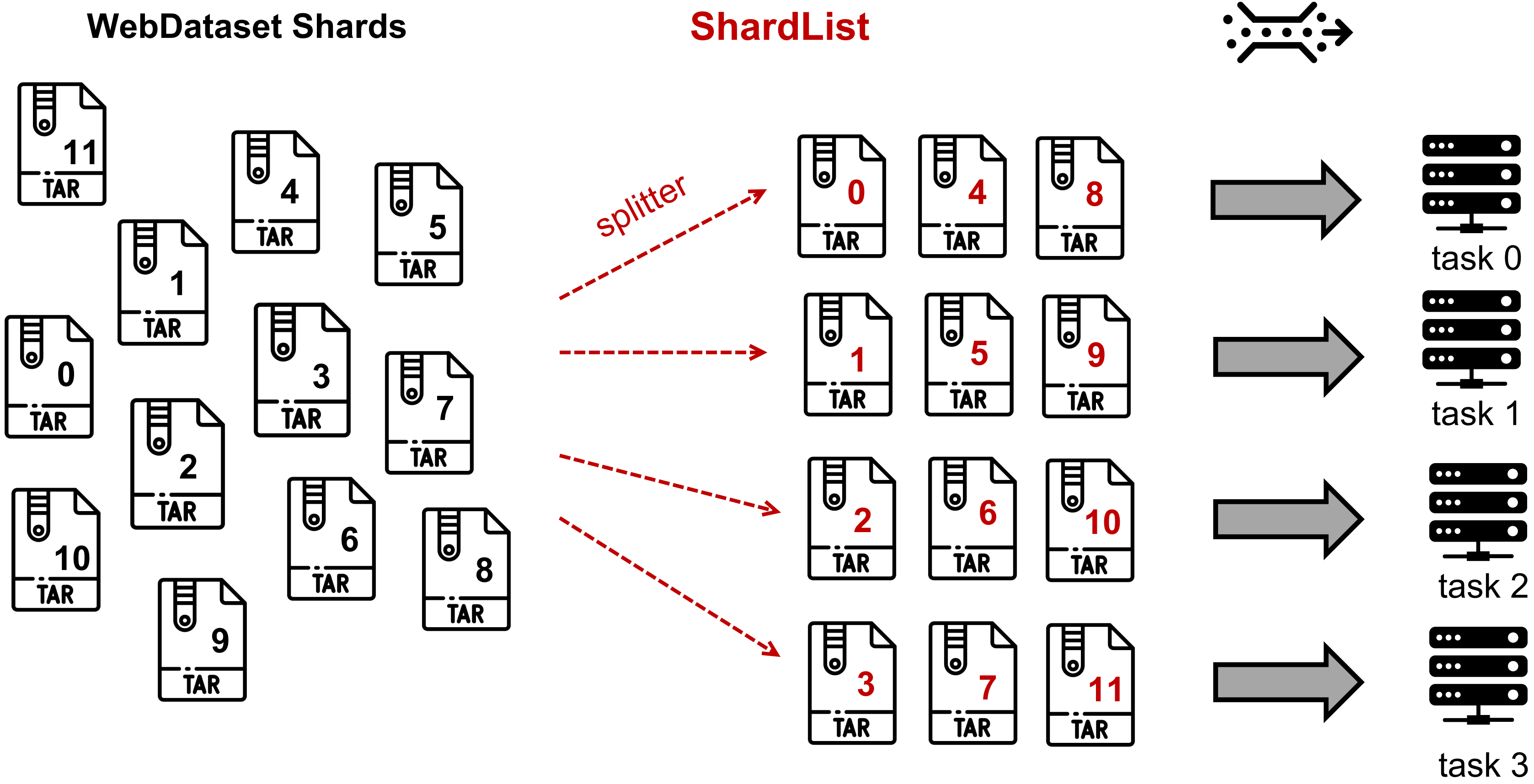
Samples must be evenly distributed among the shards to balance the workload between processes.

WebDataset format - More or less shards?

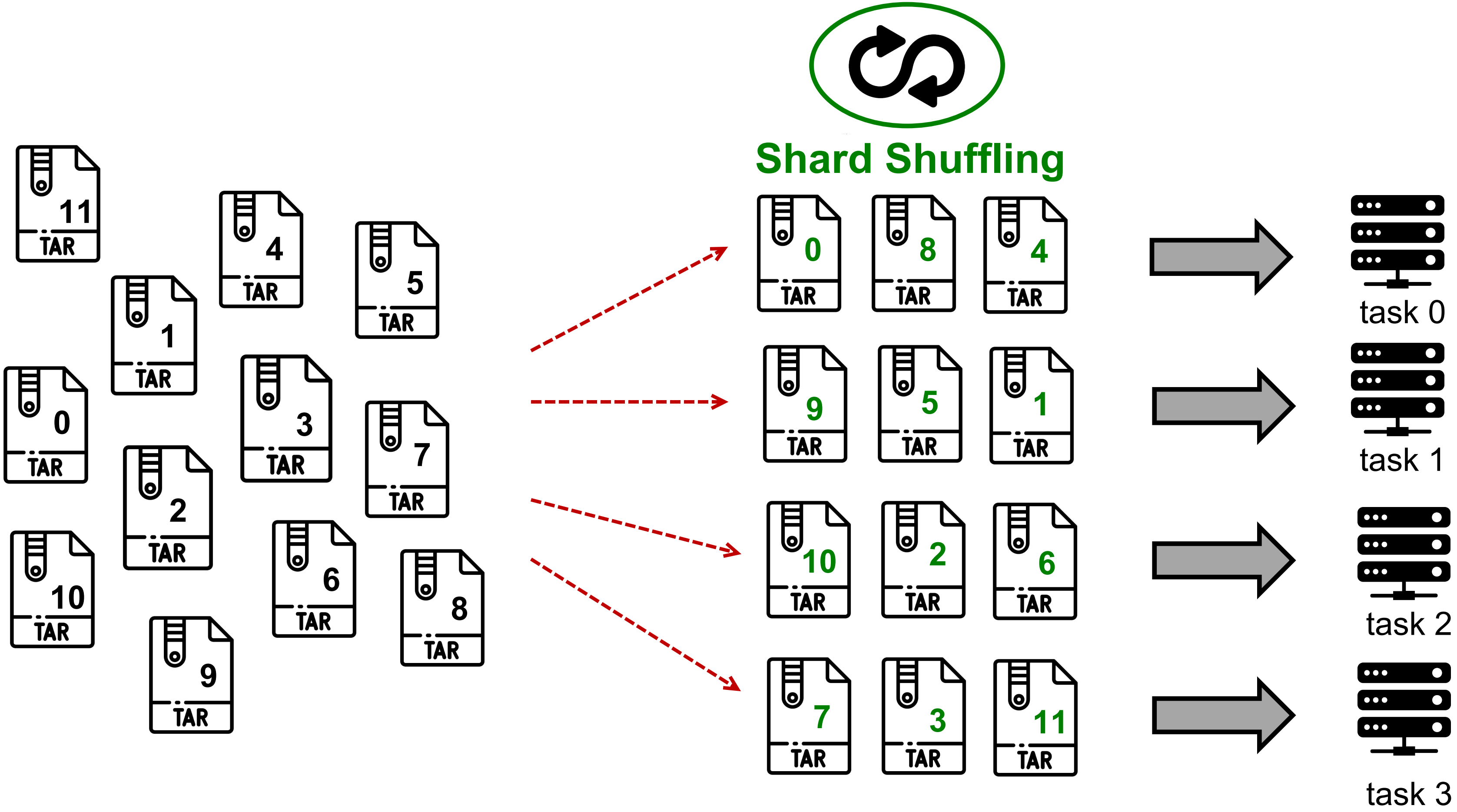
	More shards	Less shards
Large scale distribution	+	-
Shared bandwidth	+	-
Inodes quota	-	+
Number of I/O	-	+



WebDataset – Multiworker sharding



WebDataset - Shuffling



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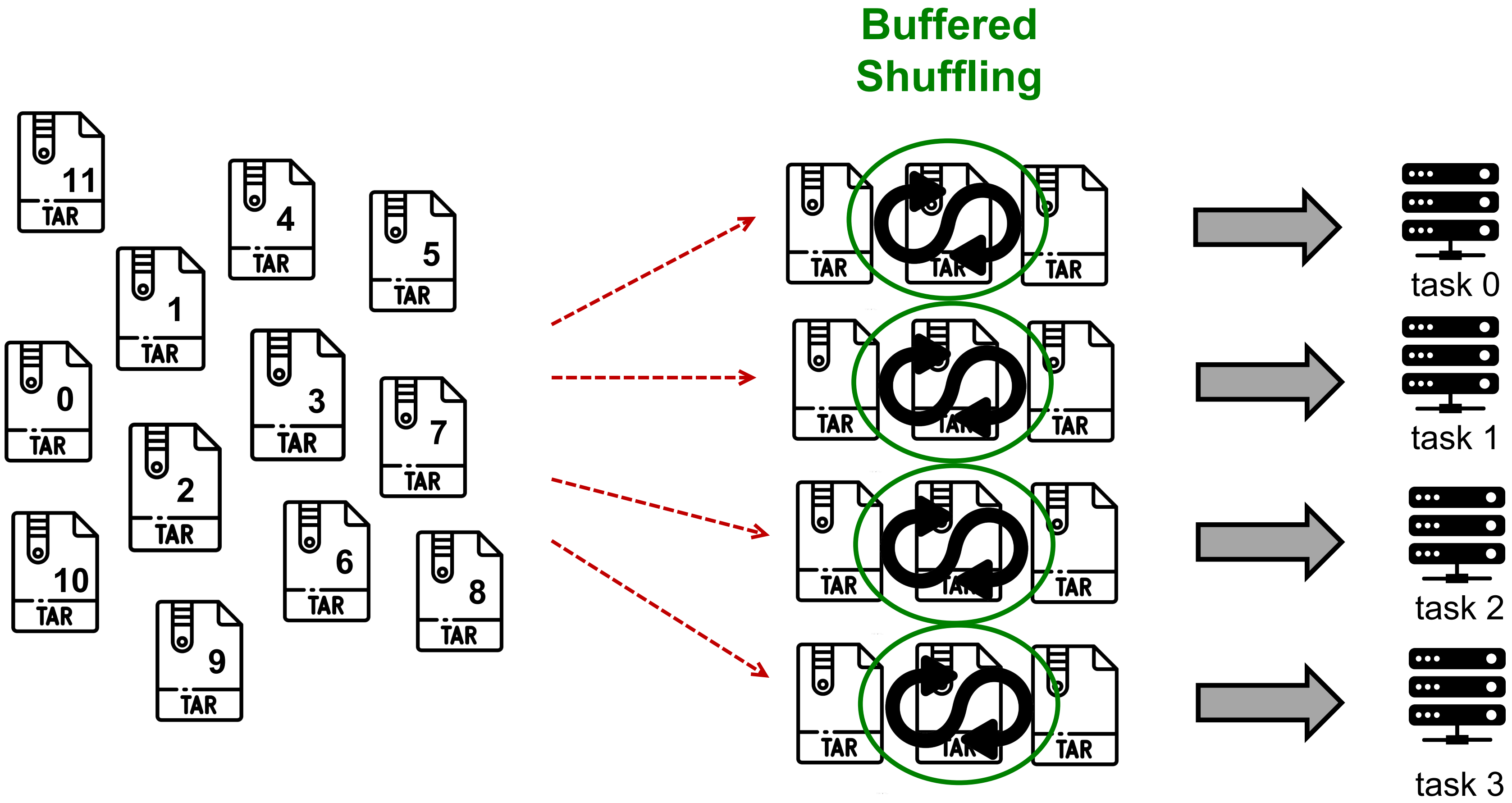
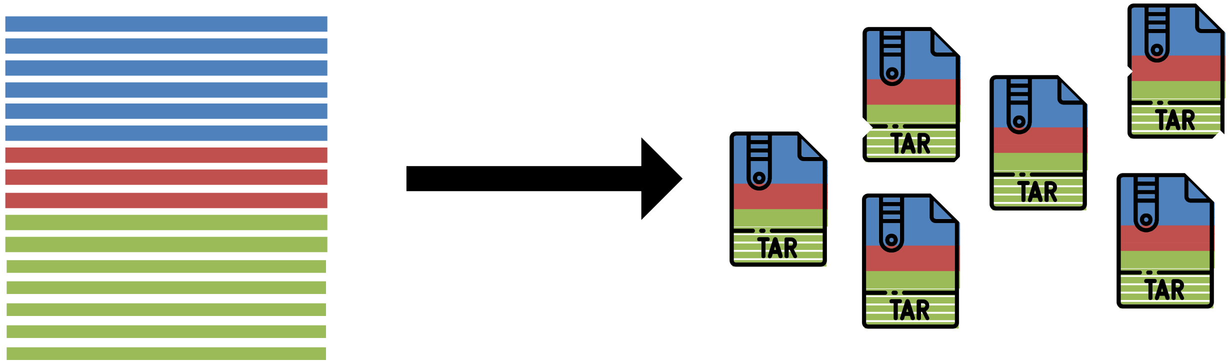


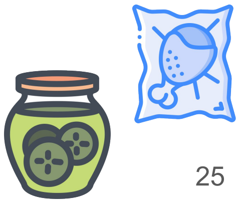
WebDataset - Generation

When generating WebDataset shards, don't forget to:

- Distribute the samples as **evenly** as possible among the shards.
- Choose the number of shards **according to the number of GPUs** you will use.
- Distribute the samples so that each shard contains a **representative part of the dataset.**



+ Converting data before creating the archives to improve decoding performance?



WebDataset - Implementation

```
import webdataset as wds

def my_splitter(paths):
    paths = list(paths)
    return paths[idr_torch.rank::idr_torch.world_size]

paths = os.environ['DSDIR']+'/imagenet/webdataset/imagenet_train-{000000..000127}.tar'
train_dataset_len = 1281167
train_dataset = wds.WebDataset(paths, nodesplitter=my_splitter, shardshuffle=True)\
                                .shuffle(1000)\
                                .decode("torchrgb")\
                                .to_tuple('input.pyd', 'output.pyd')\
                                .map_tuple(transform, lambda x: x)\
                                .batched(mini_batch_size)\
                                .with_length(train_dataset_len)

nbatches = train_dataset_len // global_batch_size
train_loader = wds.WebLoader(train_dataset, batch_size=None,\
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distribute shards among processes

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shuffling shards indexes per process

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shuffling samples per process

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description of shard content

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transforming and batching

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define len(train_dataset)

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batching handled by WebDataset class

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                             num_workers=num_workers,\
                             persistent_workers=persistent_workers,\
                             pin_memory=pin_memory,\
                             prefetch_factor=prefetch_factor\
                             ).slice(nbatches)
train_loader.length = nbatches
```

usual DataLoader args

WebDataset - Implementation

```python
import webdataset as wds

def my_splitter(paths):
    paths = list(paths)
    return paths[idr_torch.rank::idr_torch.world_size]

paths = os.environ['DSDIR']+'/imagenet/webdataset/imagenet_train-{000000..000127}.tar'
train_dataset_len = 1281167
train_dataset = wds.WebDataset(paths, nodesplitter=my_splitter, shardshuffle=True)\
                                .shuffle(1000)\
                                .decode("torchrgb")\
                                .to_tuple('input.pyd', 'output.pyd')\
                                .map_tuple(transform, lambda x: x)\
                                .batched(mini_batch_size)\
                                .with_length(train_dataset_len)

nbatches = train_dataset_len // global_batch_size
train_loader = wds.WebLoader(train_dataset, batch_size=None,\
                             num_workers=num_workers,\
                             persistent_workers=persistent_workers,\
                             pin_memory=pin_memory,\
                             prefetch_factor=prefetch_factor\
                             ).slice(nbatches)
train_loader.length = nbatches
```

drop_last equivalent

WebDataset - Implementation

```
import webdataset as wds

def my_splitter(paths):
    paths = list(paths)
    return paths[idr_torch.rank::idr_torch.world_size]

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                             num_workers=num_workers,\
                             persistent_workers=persistent_workers,\
                             pin_memory=pin_memory,\
                             prefetch_factor=prefetch_factor\
                             ).slice(nbatches)
train_loader.length = nbatches
```

define len(train_loader)

Soon in TorchData?

TorchData url

PyTorch

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Search Docs

API Reference:

Iterable-style DataPipes

Map-style DataPipes

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TorchData

Indices

TorchData

This library is part of the PyTorch project. PyTorch is an open source machine learning framework.

`torchdata` is a Beta library of common modular data loading primitives for easily constructing flexible and performant data pipelines. And, there are a few features still in prototype stage.

⚠️ **As of July 2023, we have paused active development on TorchData and have paused new releases. We have learnt a lot from building it and hearing from users, but also believe we need to re-evaluate the technical design and approach given how much the industry has changed since we began the project. During the rest of 2023 we will be re-evaluating our plans in this space. Please reach out if you suggestions or comments (please use #1196 for feedback).**

backwards compatibility.

Prototype: These features are typically not available as part of binary distributions like PyPI or Conda, except sometimes behind run-time flags, and are at an early stage for feedback and testing.

PyTorch Libraries

PyTorch

torchaudio

torchtext

torchvision

WebDataset - Perfomance test

I/O loop over the dataset
(calculation-free iterations)

```
start_time = datetime.datetime.now()

for i, (images,labels) in enumerate(loader):
    print(f'{i} / {nb_batches}', end="\r")

end_time = datetime.datetime.now()
delta_time = (end_time_it - start_time_it).total_seconds()
```

- Execution on 1 GPU

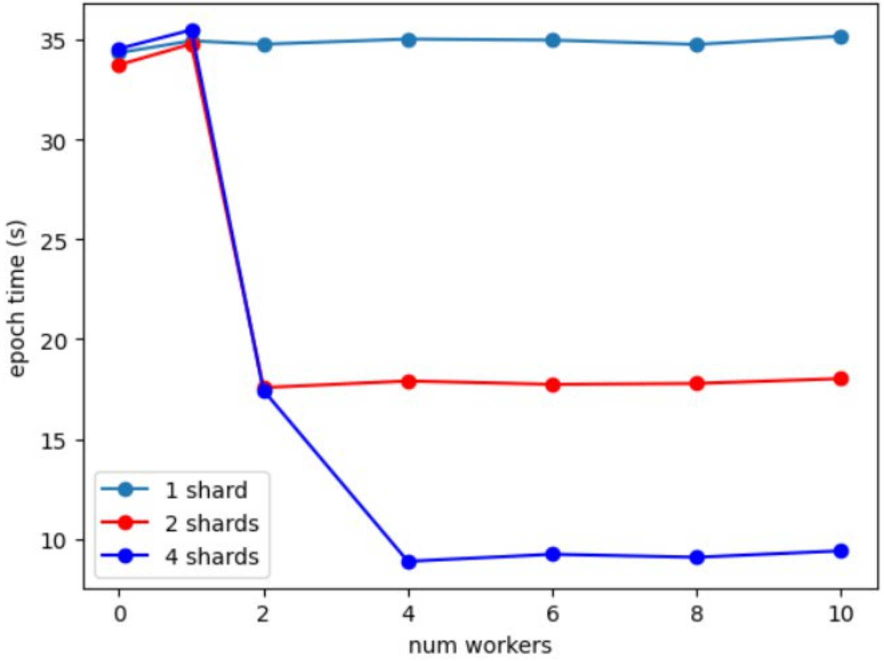
WebDataset - Perfomance test

I/O loop over the dataset
(calculation-free iterations)

CIFAR10 ~ 50k images

- Sharding is necessary to benefit from parallel implementation (DataLoader multi-processing).

CIFAR 10 (50k images)
elapsed time - 1 epoch



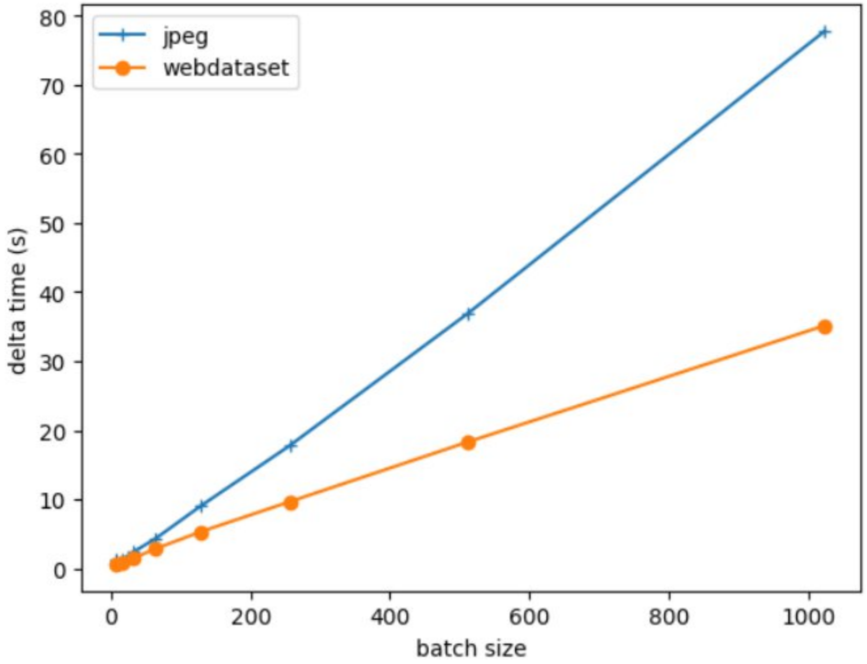
WebDataset - Perfomance test

I/O loop over the dataset
(calculation-free iterations)

Imagenet ~ 1.3M images
128 shards ~10k images per shard (+labels)
1 shard (images + labels) ~ 6GB

- The more samples are needed per batch, the more efficient is the WebDataset format (fewer I/Os).

Imagenet
elapsed time - 10 iterations



more I/O generated

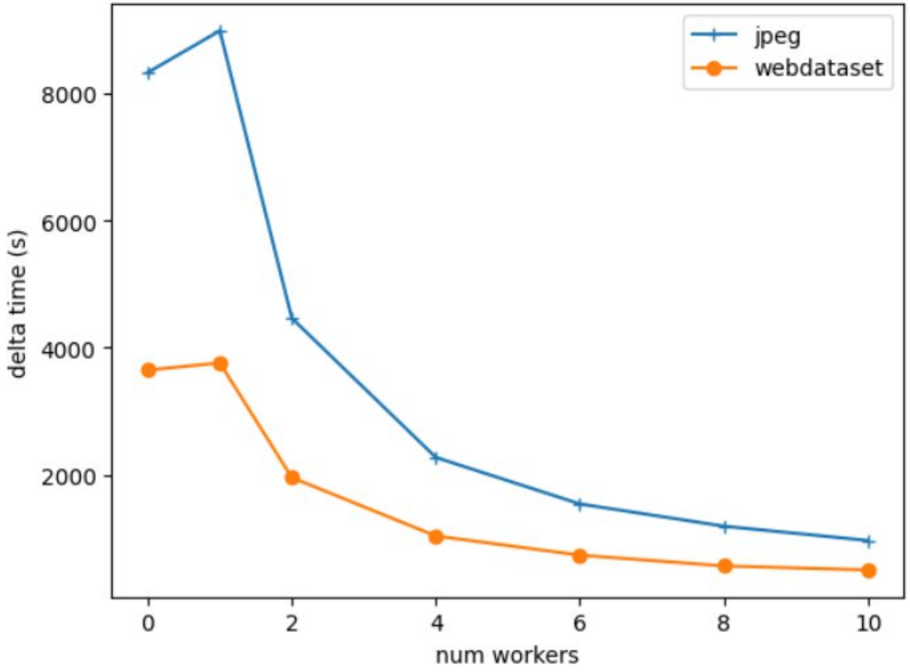
WebDataset - Perfomance test

I/O loop over the dataset
(calculation-free iterations)

Imagenet ~ 1.3M images
128 shards ~10k images per shard (+labels)
1 shard (images + labels) ~ 2GB

- The WebDataset format scales up.

Imagenet
elapsed time - 1 epoch



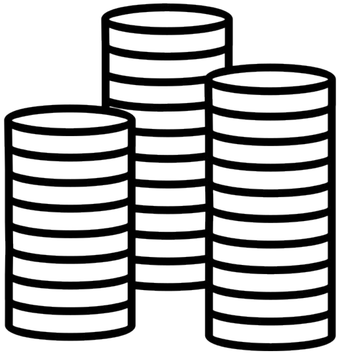
WebDataset - Perfomance test

A complete training over the Imagenet dataset (dlojz.py)

	Original jpeg dataset	WebDataset format
Elapsed time (41 epochs)	30min43s	29min56s
Test accuracy	72%	72%

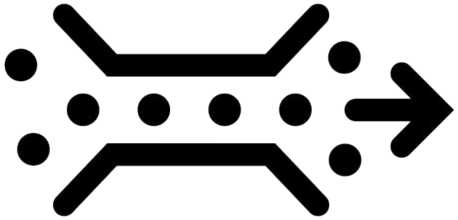
Conclusion

Storage Disks



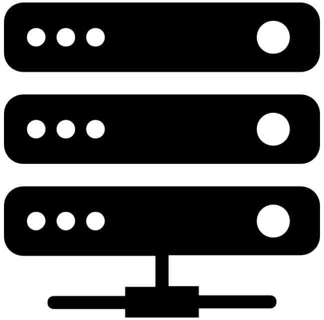
1. I/O performance

Interconnection Network
Omnipath



2. Shared Bandwidth

CPU workers



3. Decoder performance

- Disk spaces: WORK / DSDIR or SCRATCH
- Data format: binary or compressed
- Dataset format: alternative format like WebDataset

Appendix A – HuggingFace Datasets

Hugging Face Hub

`dataset = load_dataset("dataset_name")`, get any of these datasets ready to use in a dataloader for training/evaluating a ML model (Numpy/Pandas/PyTorch/TensorFlow/JAX) - **from remote access or from local copy**.

Two types of dataset objects: **Dataset** or **IterableDataset** .

- **IterableDataset** is ideal for big datasets (think hundreds of GBs!)
- **Dataset** is great for everything else.

General :

- In-memory data (dictionary, Pandas DataFrames, generator)
- CSV
- JSON
- Parquet
- Arrow
- SQL
- **WebDataset**

Audio :

- Local Files Dictionary
- AudioFolder
- AudioFolder with metadata

Text :

- Text Files list
- TextFolder

Vision :

- Local Files Dictionary
- ImageFolder
- **WebDataset**

Tabular :

- CSV files
- Pandas DataFrames
- Databases (SQLite, PostgreSQL)

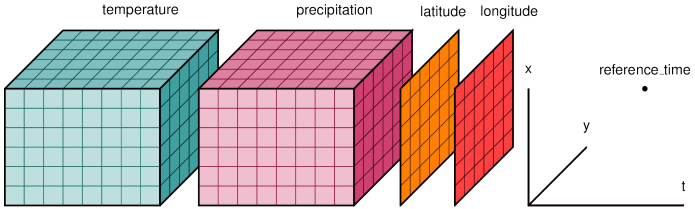
https://huggingface.co/docs/datasets/index

Appendix B – ESPRI-IA Use Case

Context : Large Training Scientific Dataset

NetCDF (network Common Data Form) is a file format for **storing multidimensional scientific data** (variables) such as temperature, humidity, pressure, wind speed, and direction.

Xarray is a library for working with domain-agnostic data-structures, labeled arrays, NetCDF, Zarr, ...



Test :

Storage format : Numpy, HDF5, WebDataset, Zarr

Zarr is a high-level storage format
Dataset-level abstraction with indexing

High-performance Compressor : BLOSC + LZ4

BLOSC is a meta-Compressor

Slide: https://espri.ipsl.fr/wp-content/uploads/2023/12/storage_formats.pdf
video: https://www.youtube.com/watch?v=w8TJcBf87zw

Appendix B – ESPRI-IA Use Case

Conclusion:

with BLOSC + LZ4, loading (I/O + com + decoding) compressed data is faster than loading uncompressed data! Recommended for WebDataset and Zarr!

For Short Dataset:
Numpy/Pickle is the best suitable storage format !!

For Long Dataset:
- Map style: **Zarr >** HDF5
- Iterable: **WebDataset >** Zarr ≈ HDF5

Slide: https://espri.ipsl.fr/wp-content/uploads/2023/12/storage_formats.pdf
video: https://www.youtube.com/watch?v=w8TJcBf87zw

Annex – Attempt at Standardization

- TorchData?

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- MLCommons/Croissant

Croissant 🥐 is a high-level format for machine learning datasets that combines metadata, resource file descriptions, data structure, and default ML semantics into a single file; it works with existing datasets to make them easier to find, use, and support with tools.

Croissant builds on schema.org, and its Dataset vocabulary, a widely used format to represent datasets on the Web, and make them searchable.

Croissant is currently under development by the community.

Since Jul. 2023