Deep Learning Optimized on Jean Zay

Dataset optimization

Storage spaces and data format

CNRS

IDRIS

Dataset optimization

Main bottlenecks ◀

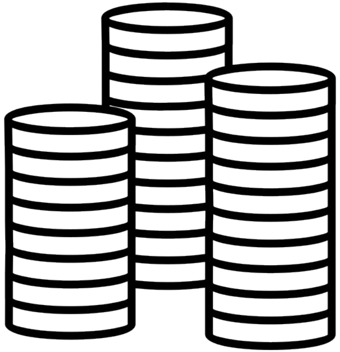
Data storage – various disk spaces ◀

Data format – at sample level ◀

Data format – at dataset level ◀

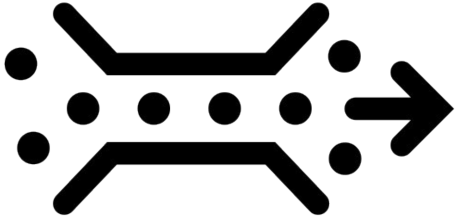
Bottlenecks upstream of DataLoader

Storage Disks



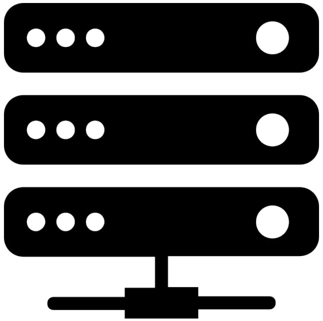
1. I/O performance

Interconnection Network
Omnipath



2. Shared Bandwidth

CPU workers



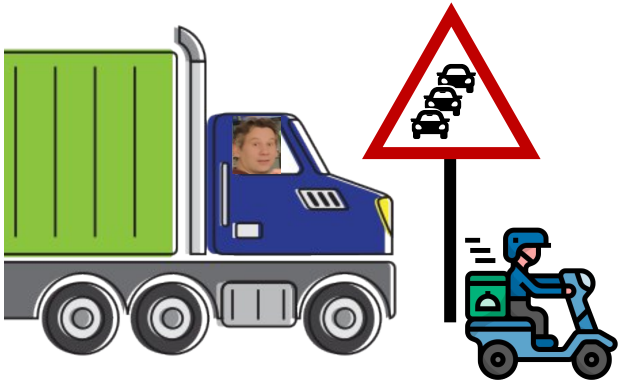
3. Decoder performance

Bottlenecks upstream of DataLoader

Storage Disks

1. I/O performance

Interconnection Network
Omnipath



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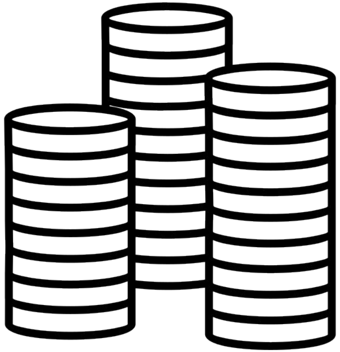

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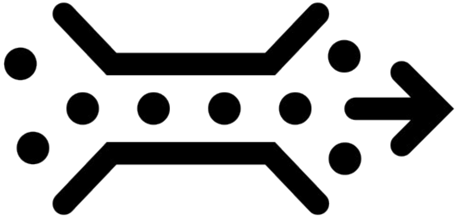

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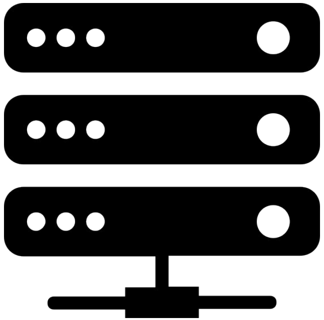
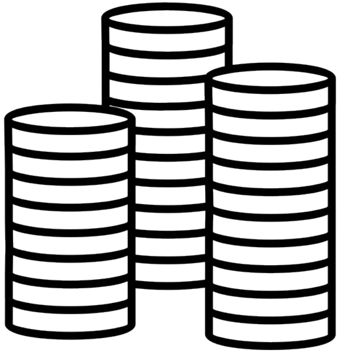


3. Decoder performance

Where should I store my dataset?

Various disk spaces

Storage Disks



1. I/O performance

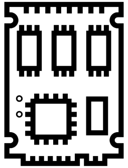
WORK

Rotative disk spaces

100 GB/s
OPA

SCRATCH / DSDIR

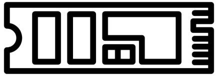
Full Flash



500 GB/s
OPA

NVMe

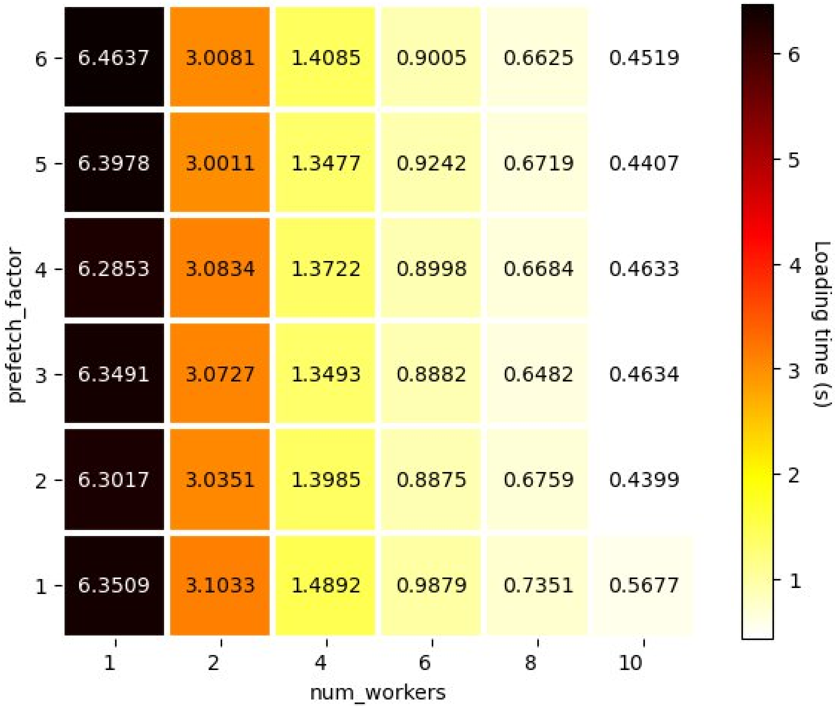
Local disk
(test configuration)

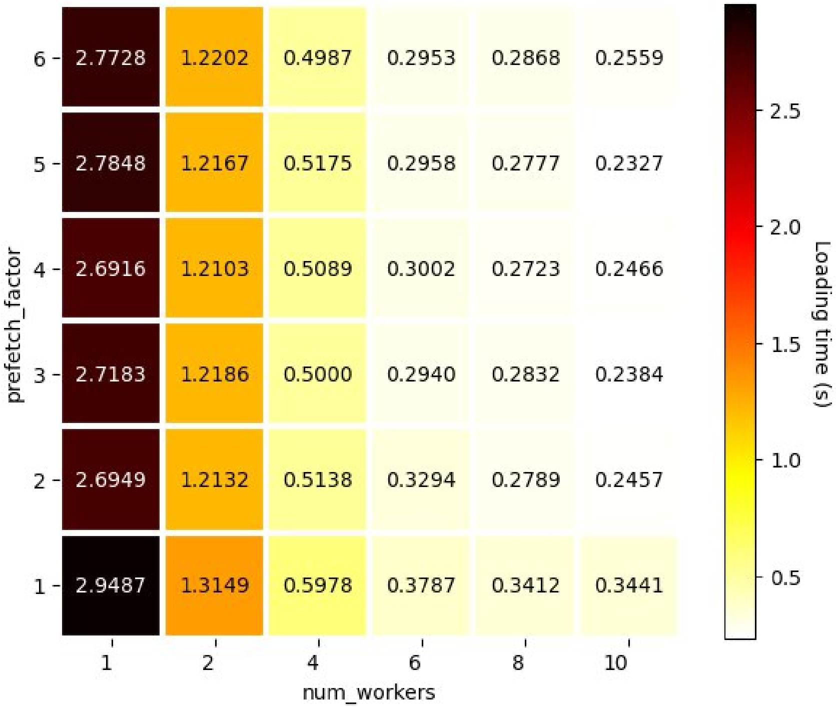


PCIe

Various disk spaces

dlojz.py - 50 iterations - test partition gpu_p4





WORK

100 GB/s - OPA

÷ 2

SCRATCH

500 GB/s - OPA

Various disk spaces

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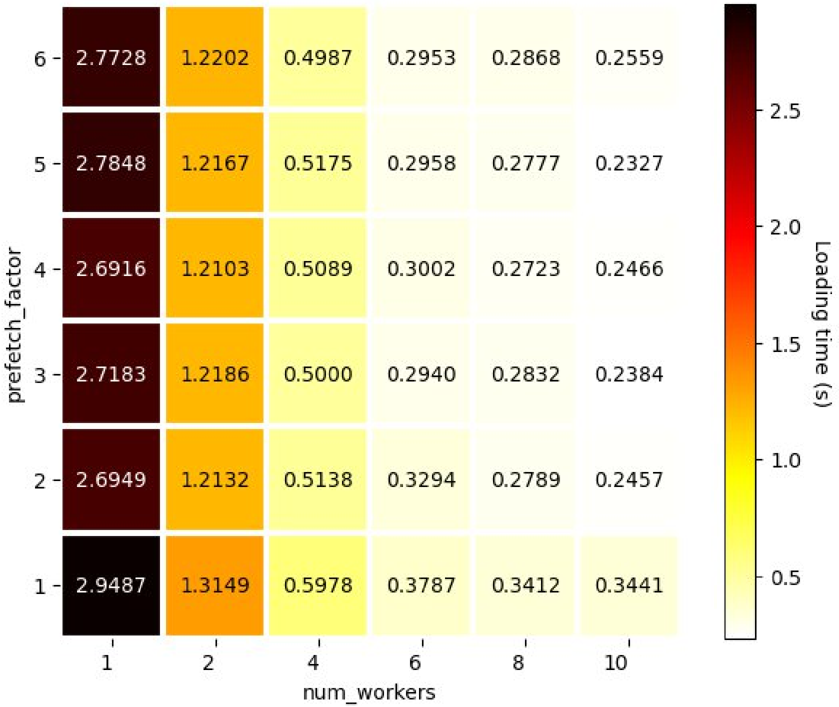
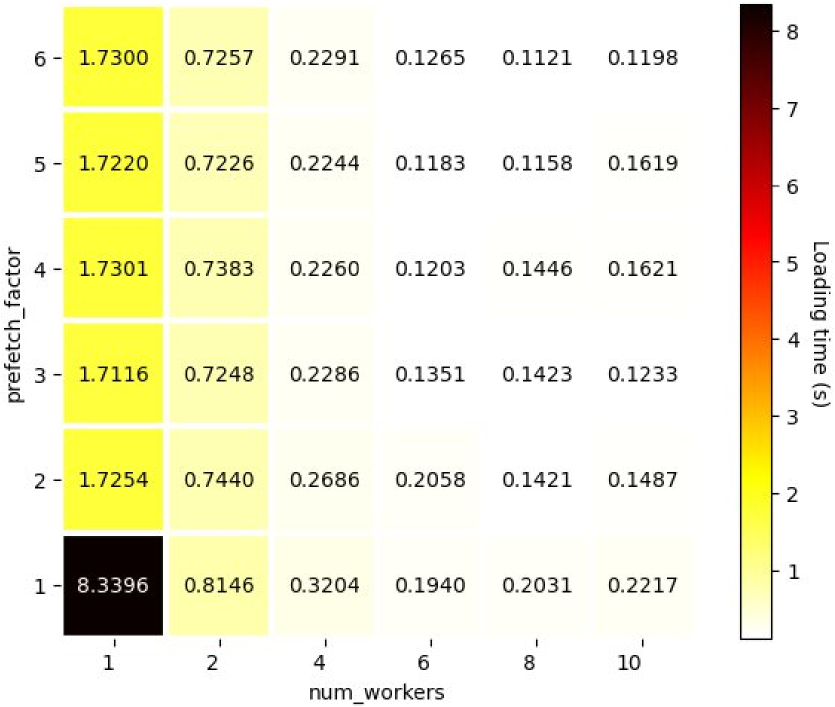




SCRATCH

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**
  - – 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 ◀

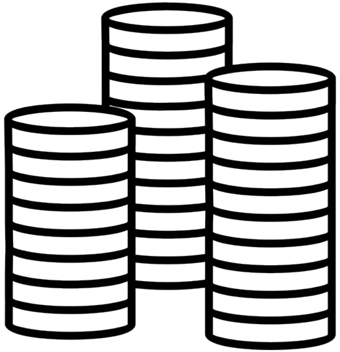
Data storage – various disk spaces ◀

Data format – at sample level ◀

Data format – at dataset level ◀

Bottlenecks upstream of DataLoader

Storage Disks



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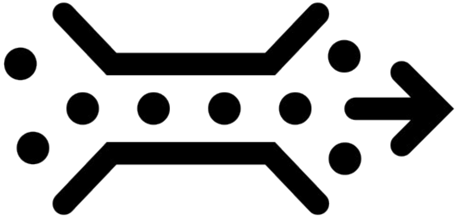
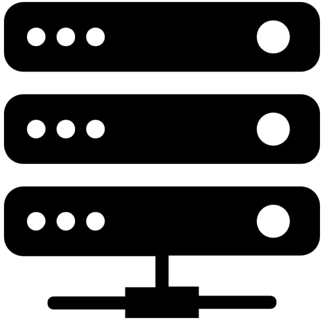


2. Shared Bandwidth

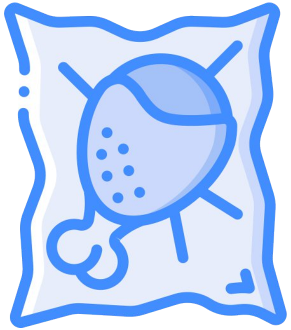
CPU workers



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

Main bottlenecks ◀

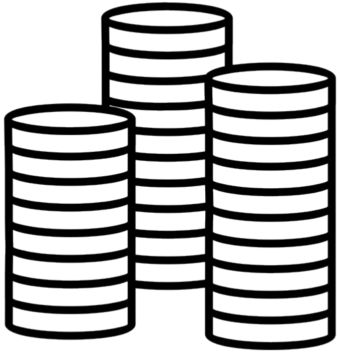
Data storage – various disk spaces ◀

Data format – at sample level ◀

Data format – at dataset level ◀

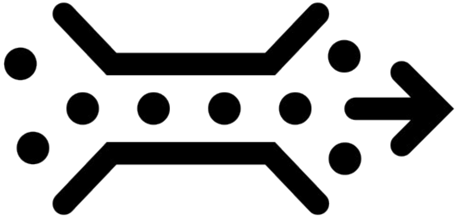
Bottlenecks upstream of DataLoader

Storage Disks



1. I/O performance

Interconnection Network
Omnipath



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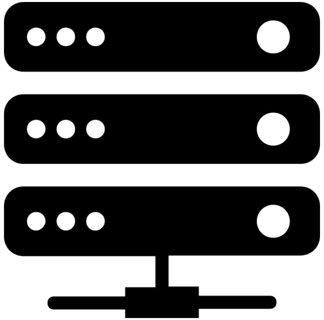


3. Decoder performance

Which format for my dataset?

Imagenet case

Supervised Learning

Goal:

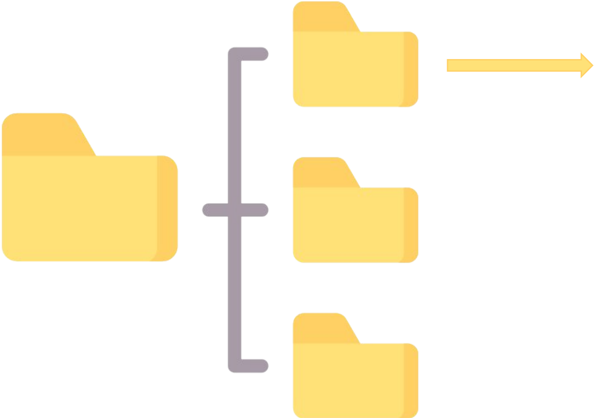
Classification (1000 classes)

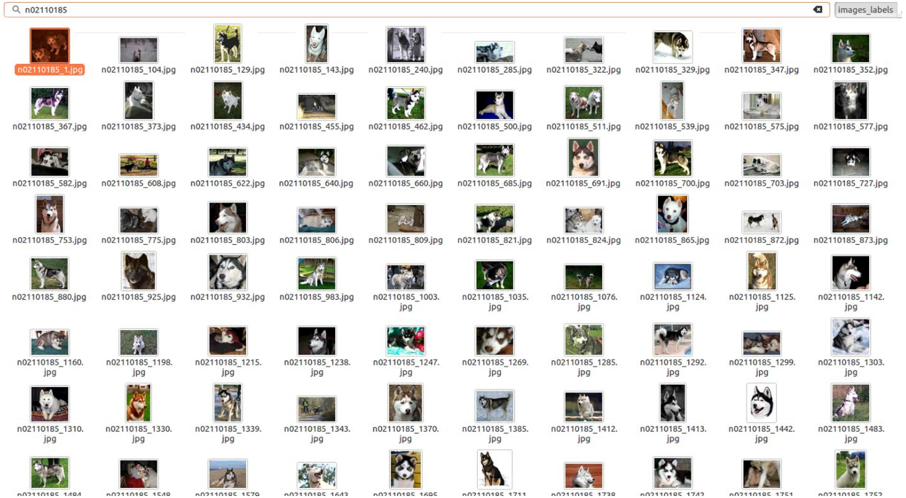
Dataset:

Train dataset: **1,2 M** labeled images

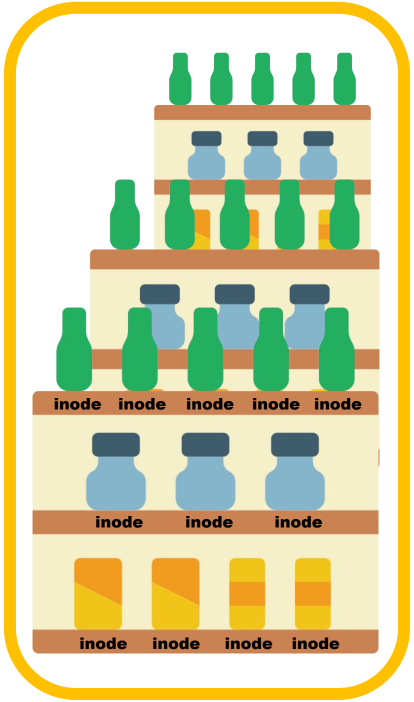
Validation dataset: **50 000** labeled images

http://www.image-net.org/





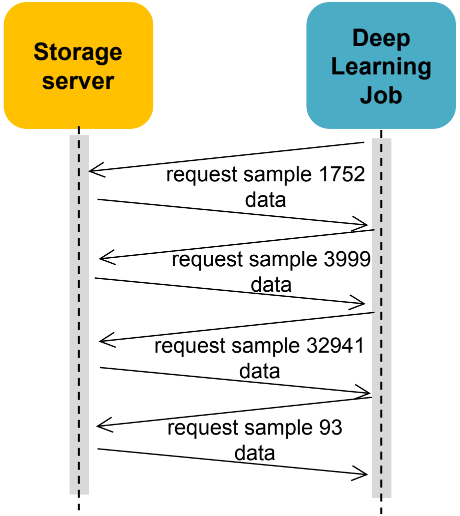
Intuitive way

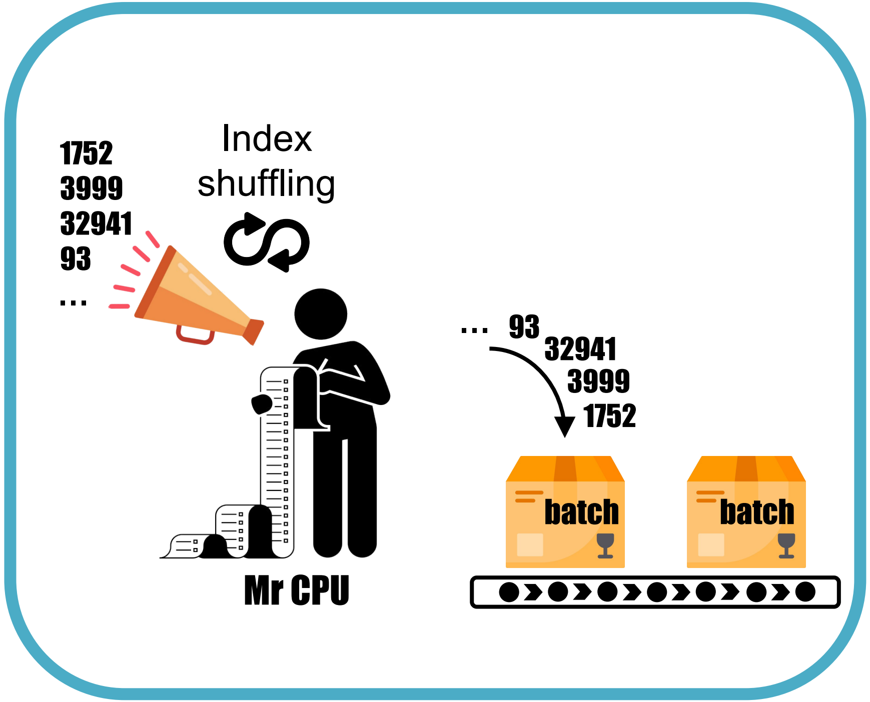


Map-style dataset

__getitem__

Random Access
to File Store



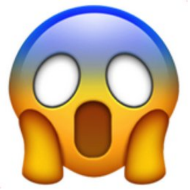


Pros: Easy to handle, random access possible

Cons: Lots of inodes, lots of I/Os

Too many inodes is an issue

Error: Disk quota exceeded

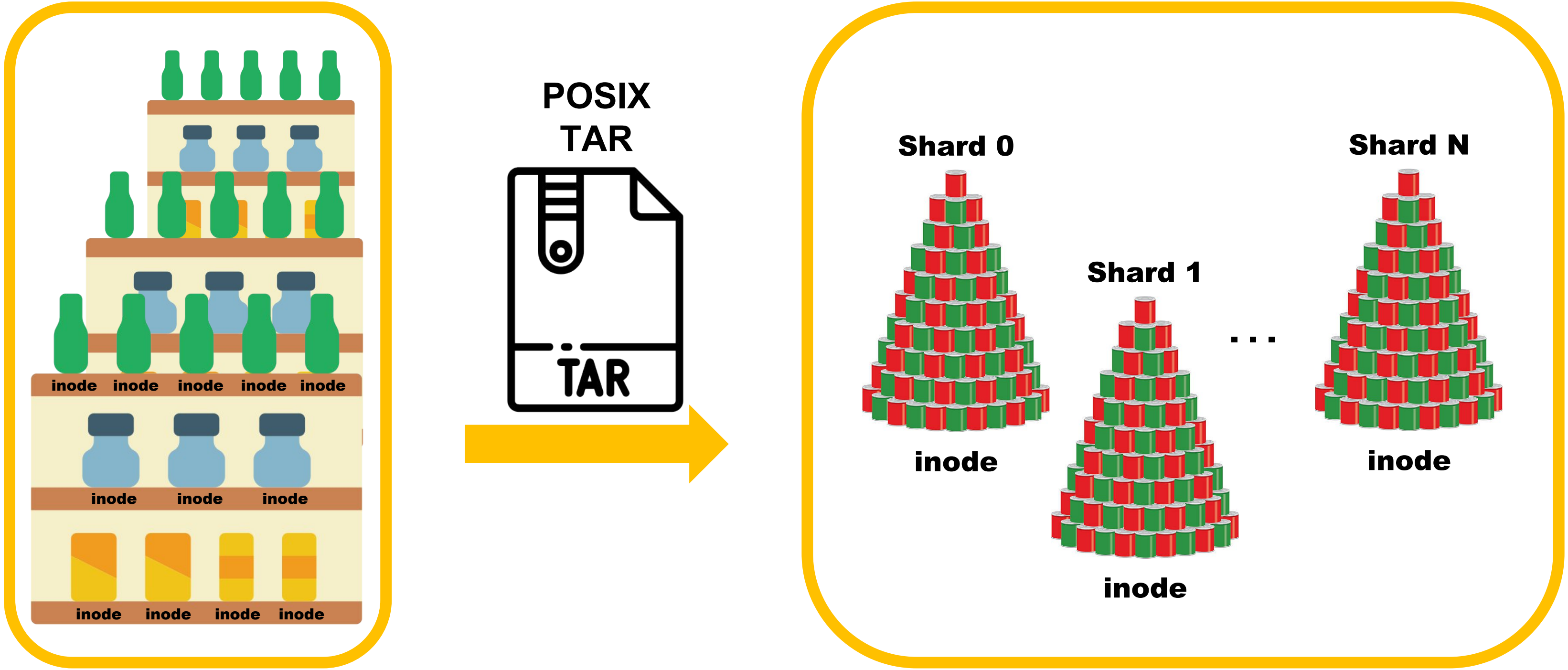


Reminder:

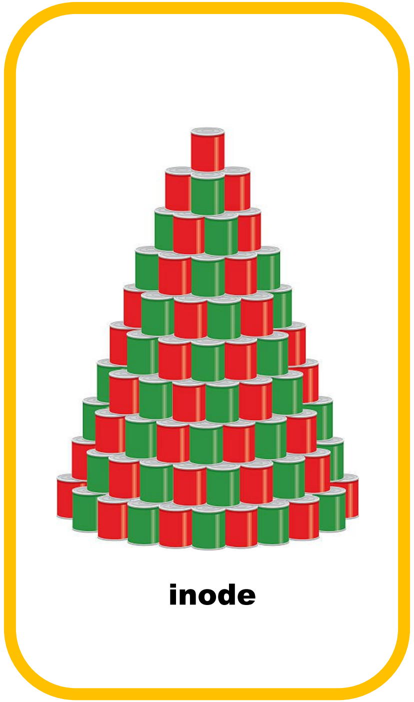
- $WORK quota per user is 5 TB / **500 kinodes**
- $SCRATCH safety quota per user is 250TB / **150 Minodes**

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

WebDataset format – Gathering inodes

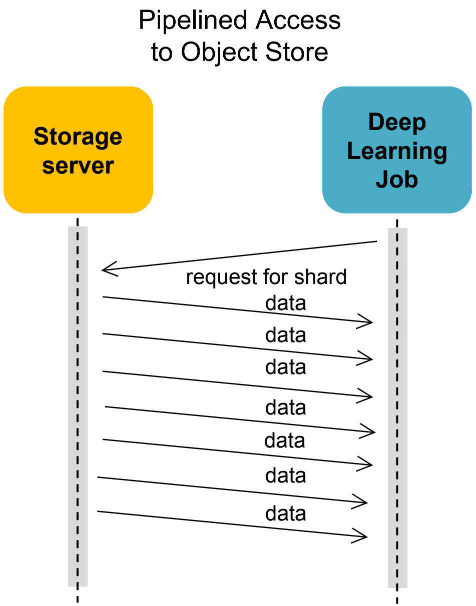


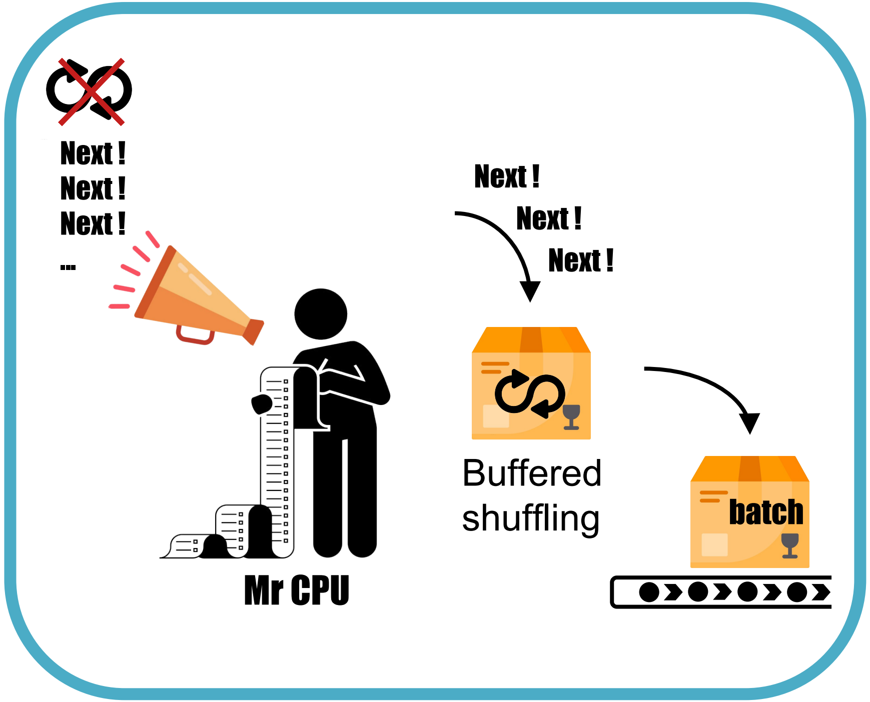
WebDataset format – Iterable dataset



Iterable-style dataset

__iter__



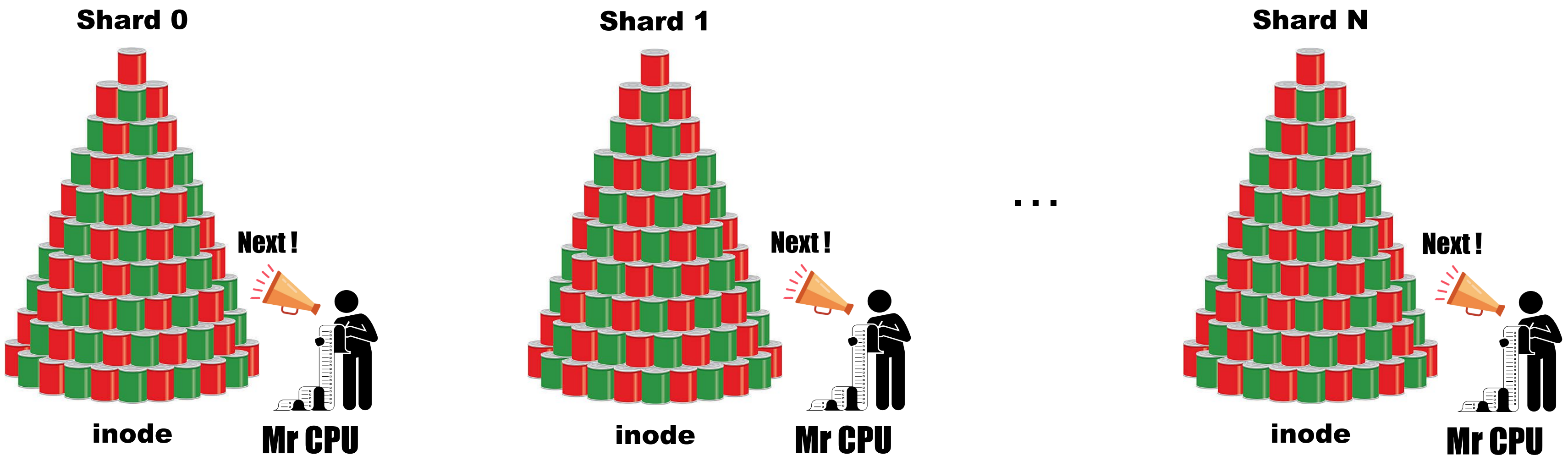


Pros: Fewer I/Os, fewer inodes

Cons: **Preprocessing**, difficult to shuffle or distribute, unknown dataset length

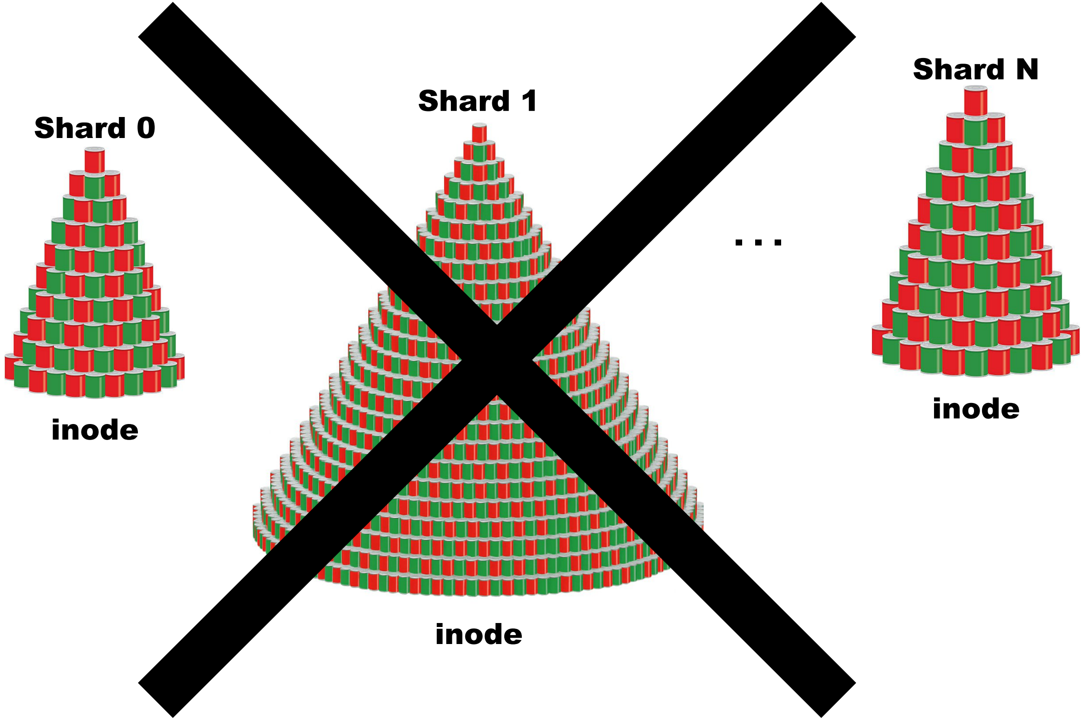
WebDataset format - Sharding

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



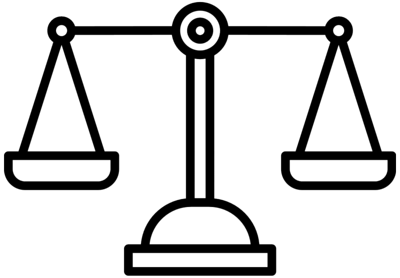
The number of shards should be a multiple of the number of tasks/GPUs.

WebDataset format - Sharding

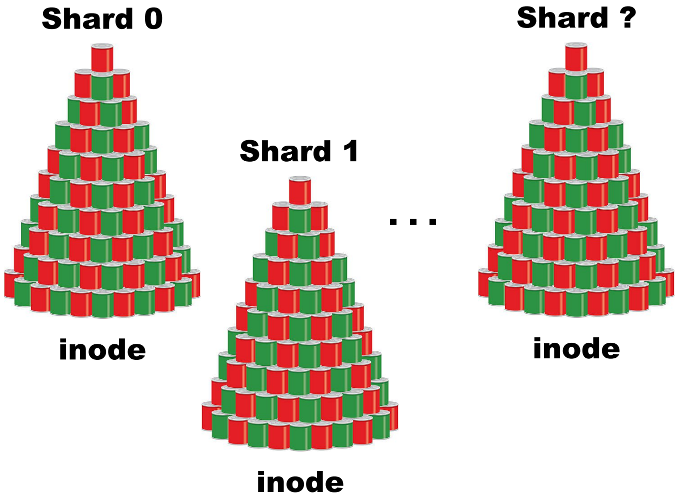


Samples must be evenly distributed among the shards to balance the workload between processes.

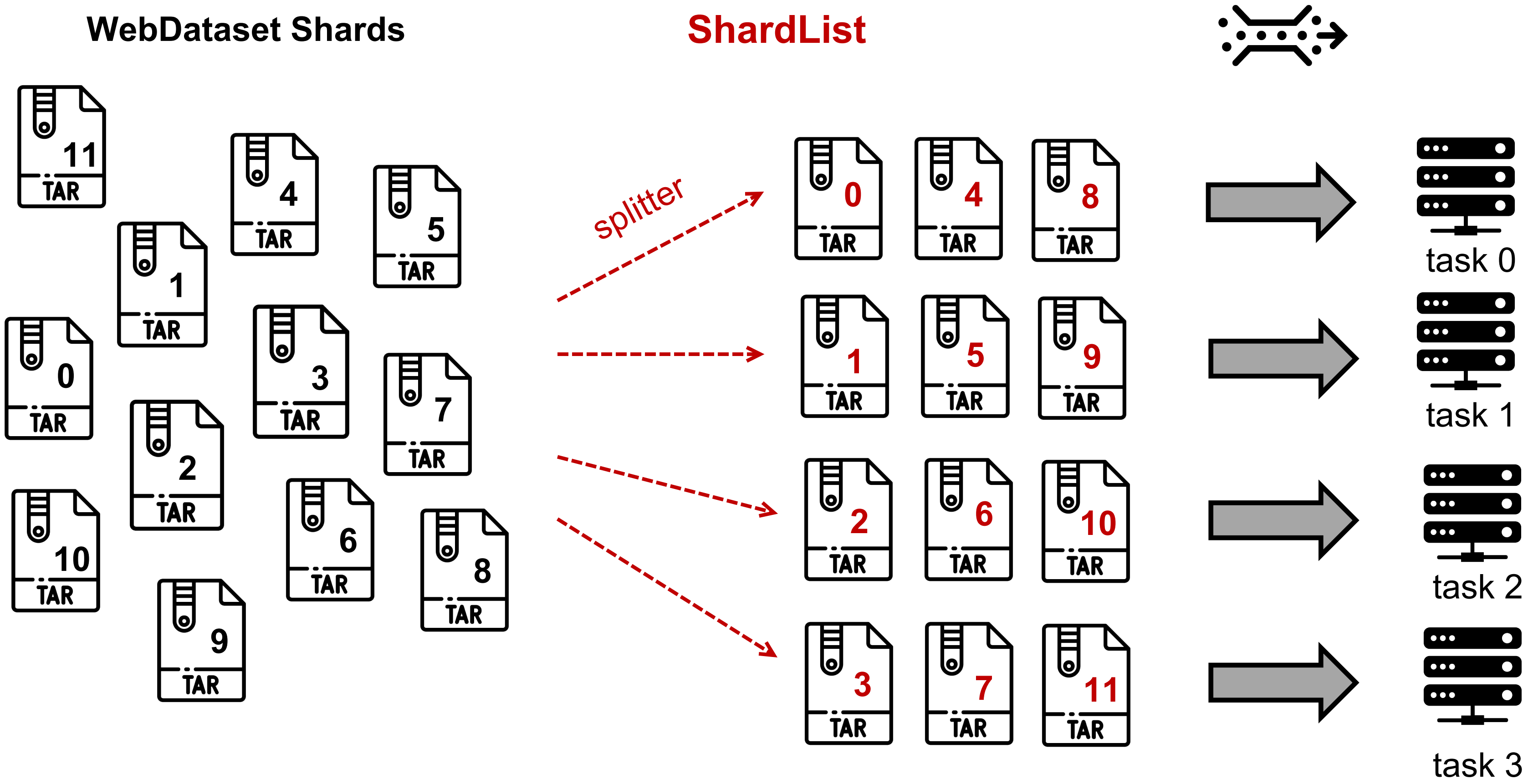
WebDataset format - More or less shards?



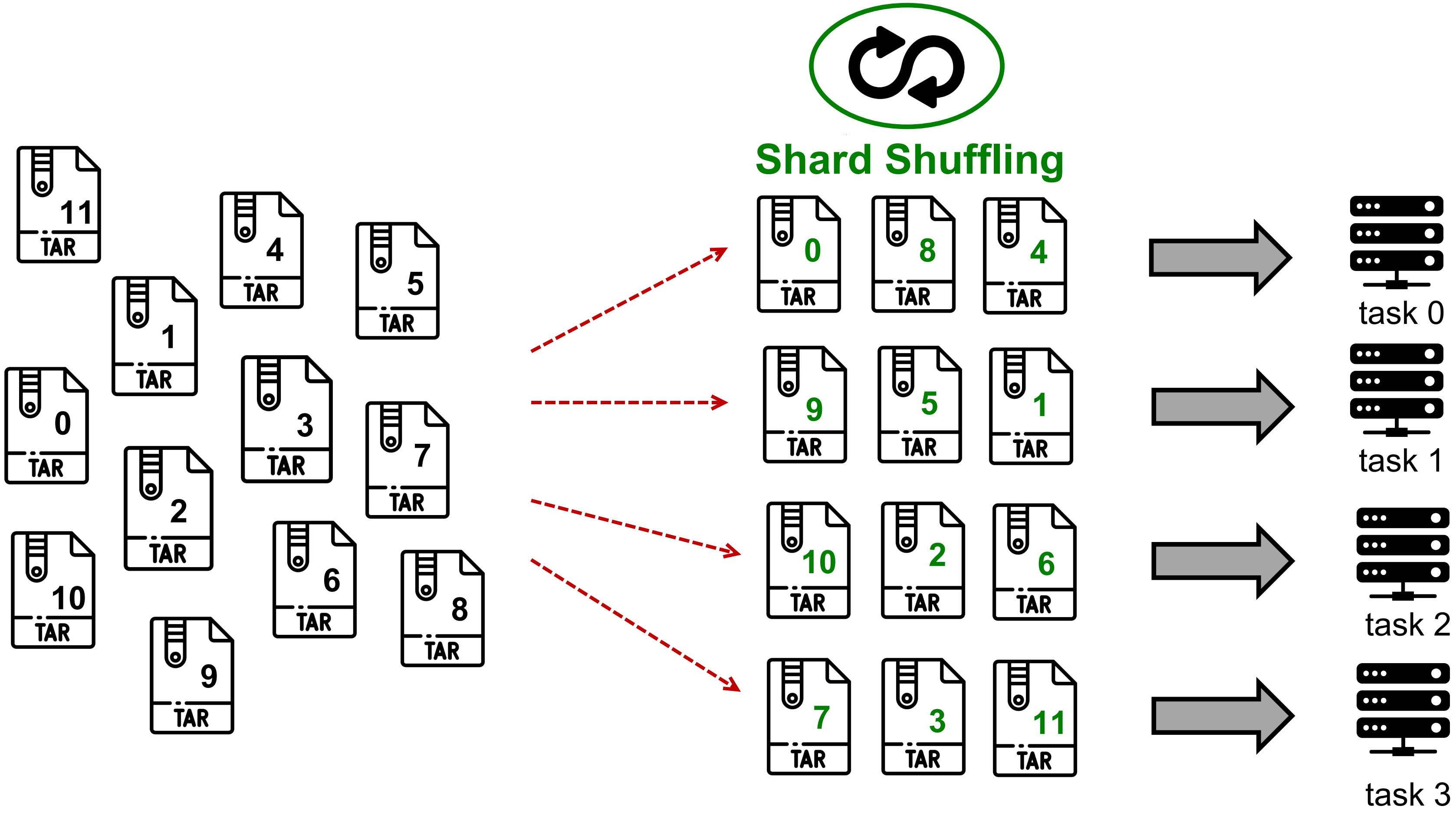
	More shards	Less shards
Large scale distribution	+	-
Shared bandwidth	+	-
Inodes quota	-	+
Number of I/O	-	+



WebDataset – Multiworker sharding



WebDataset - Shuffling



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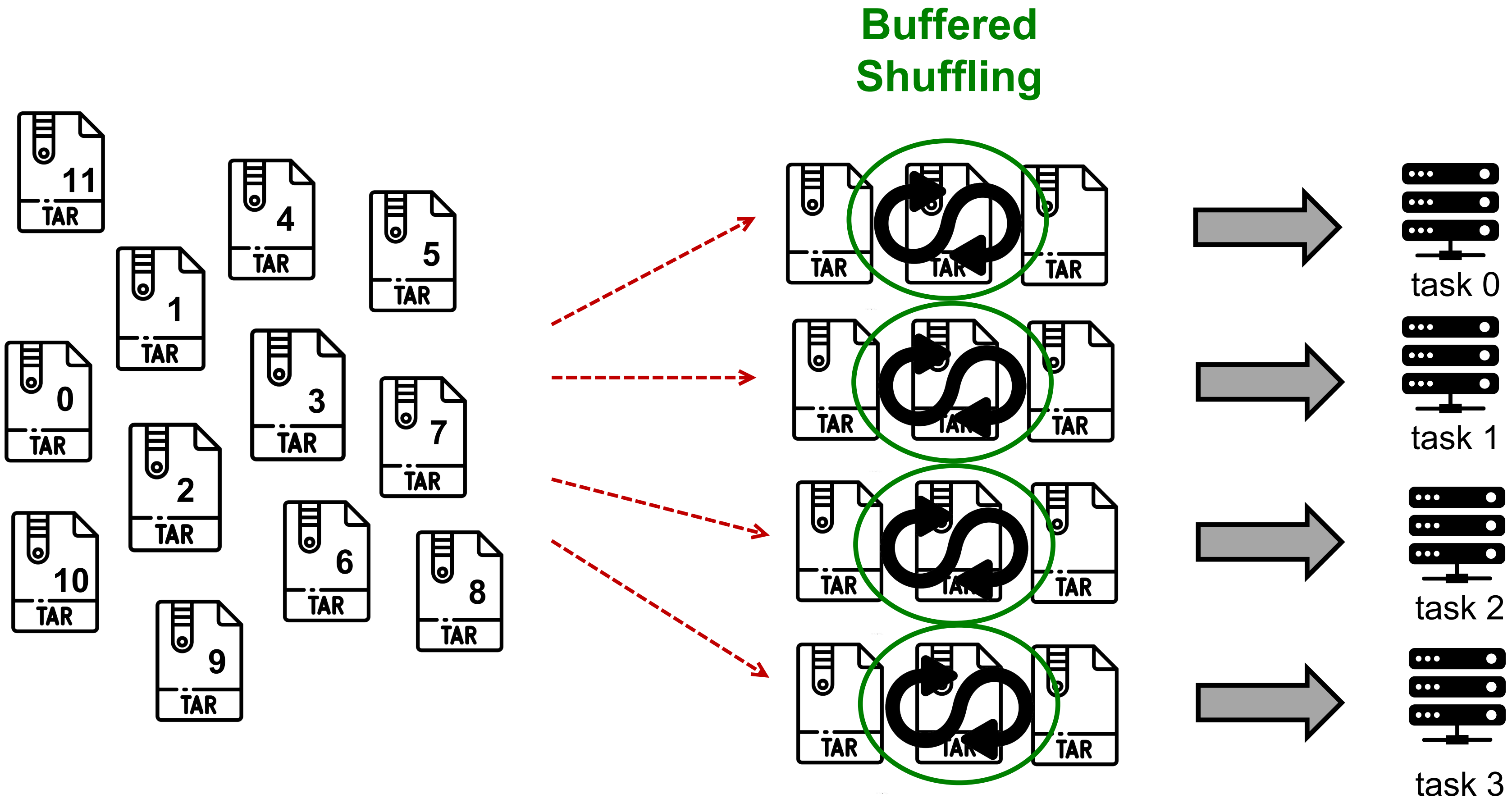
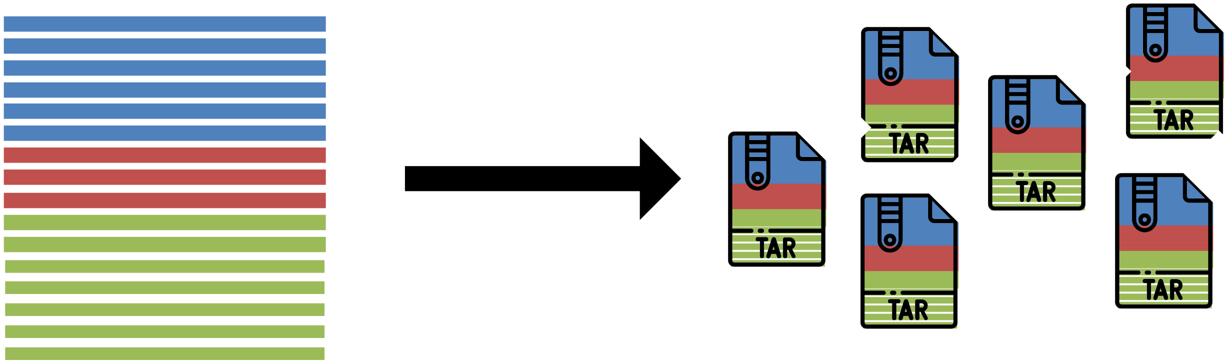
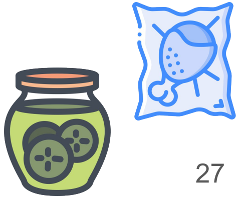


WebDataset - Preprocessing

- Distribute the samples as **evenly** as possible among the shards.
- Choose the number of shards **according to the number of GPUs & dataloader workers** 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

```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,\
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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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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
```

batching handled by WebDataset class

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

usual DataLoader args

WebDataset - Implementation

```
import webdataset as wds

def my_splitter(paths):
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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
```

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]

paths = os.environ['DSDIR']+'/imagenet/webdataset/imagenet_train-{000000..000127}.tar'
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                                .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
```

define len(train_loader)

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()
```

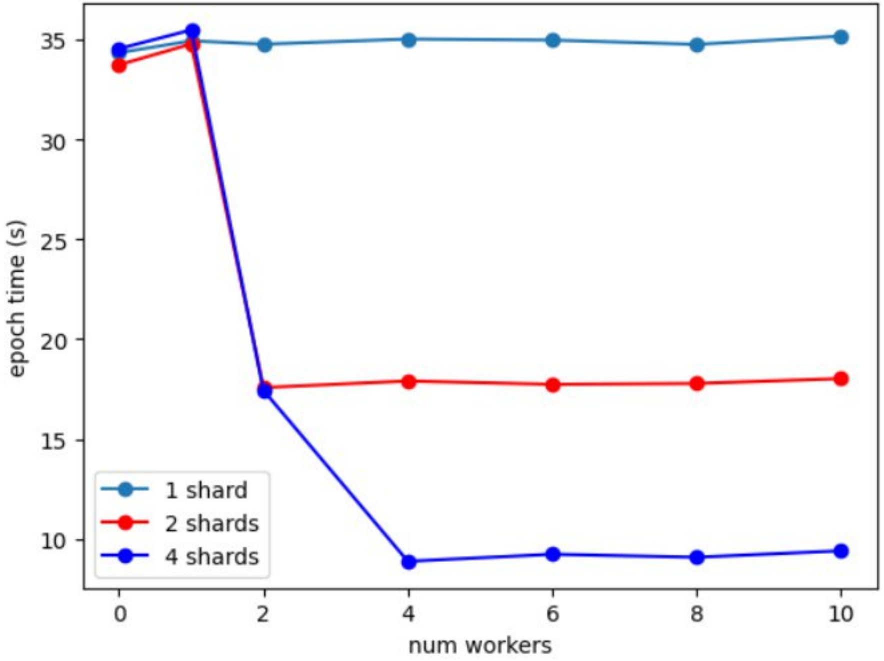
- Execution on 1 GPU

WebDataset - Perfomance test

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

CIFAR10 ~ 50k images

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



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

WebDataset - Perfomance test

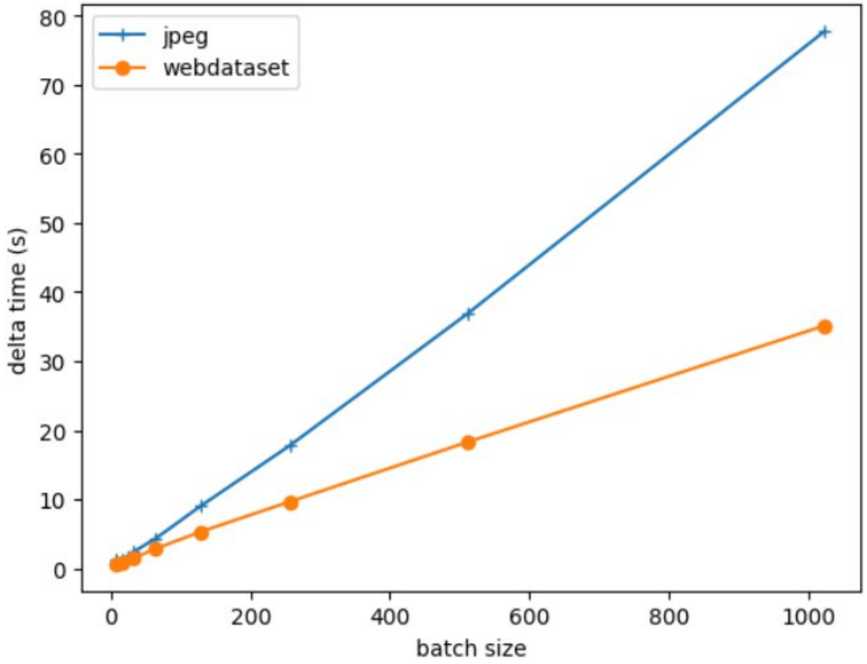
x2

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

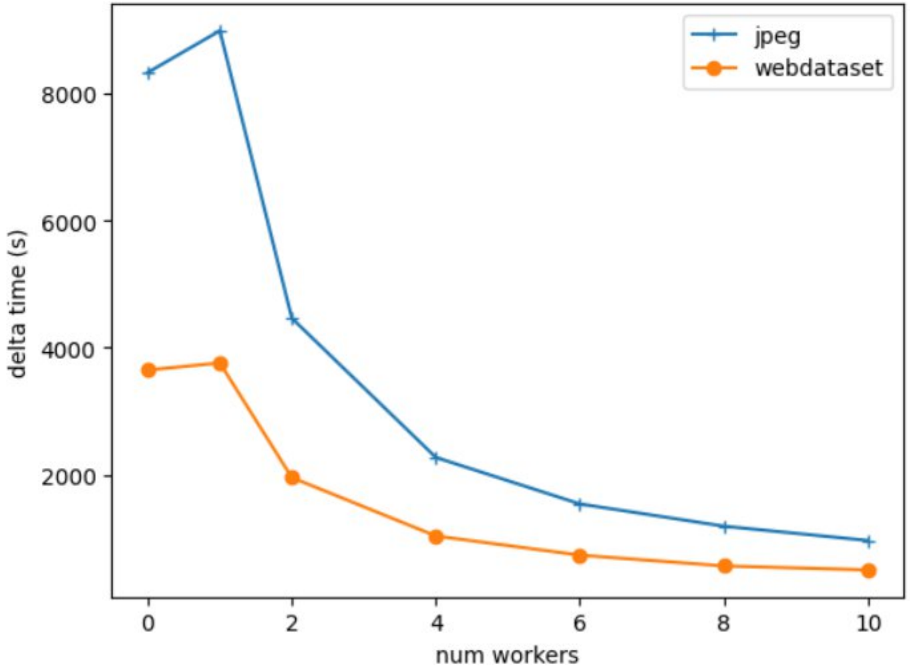
x2

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%

Other cases ?

Supervised Learning

Tabular

Texts

Audio

Video

Image 3D

. ...

?

Auto-supervised Learning

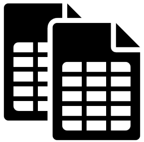
Masked Learning

Shuffling ?

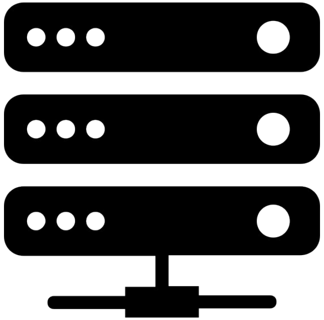
Other Formats – In-Memory Dataset

CPU workers

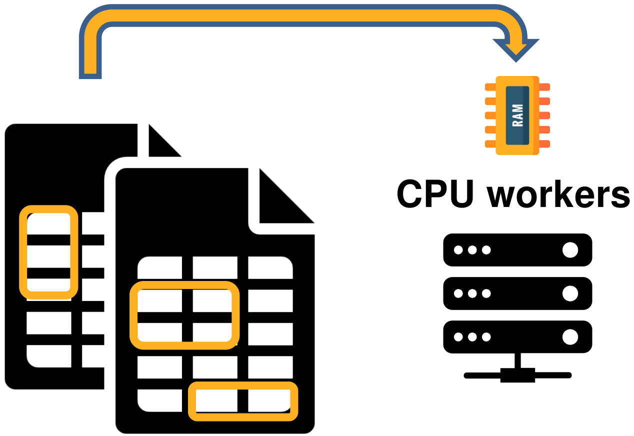
Tiny Dataset



CSV, PandasDF, Pickele,
Safetensor, GGUF



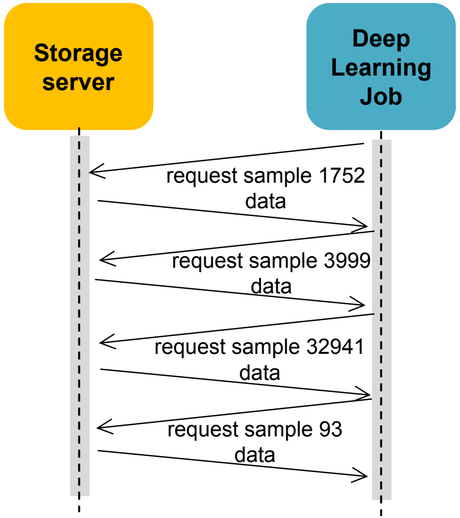
Other Formats – Chunkable formats



Large Dataset
Metadata

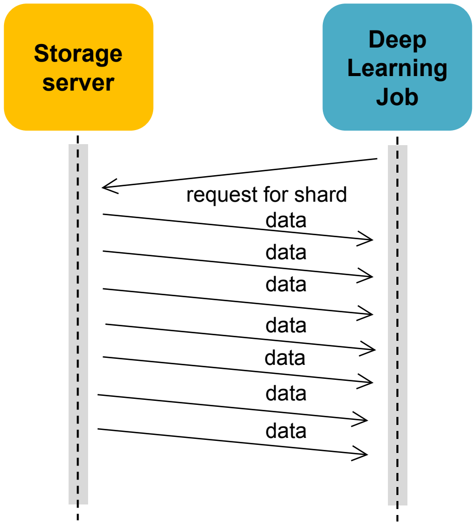
Map-style dataset
__getitem__

Random Access
to File Store



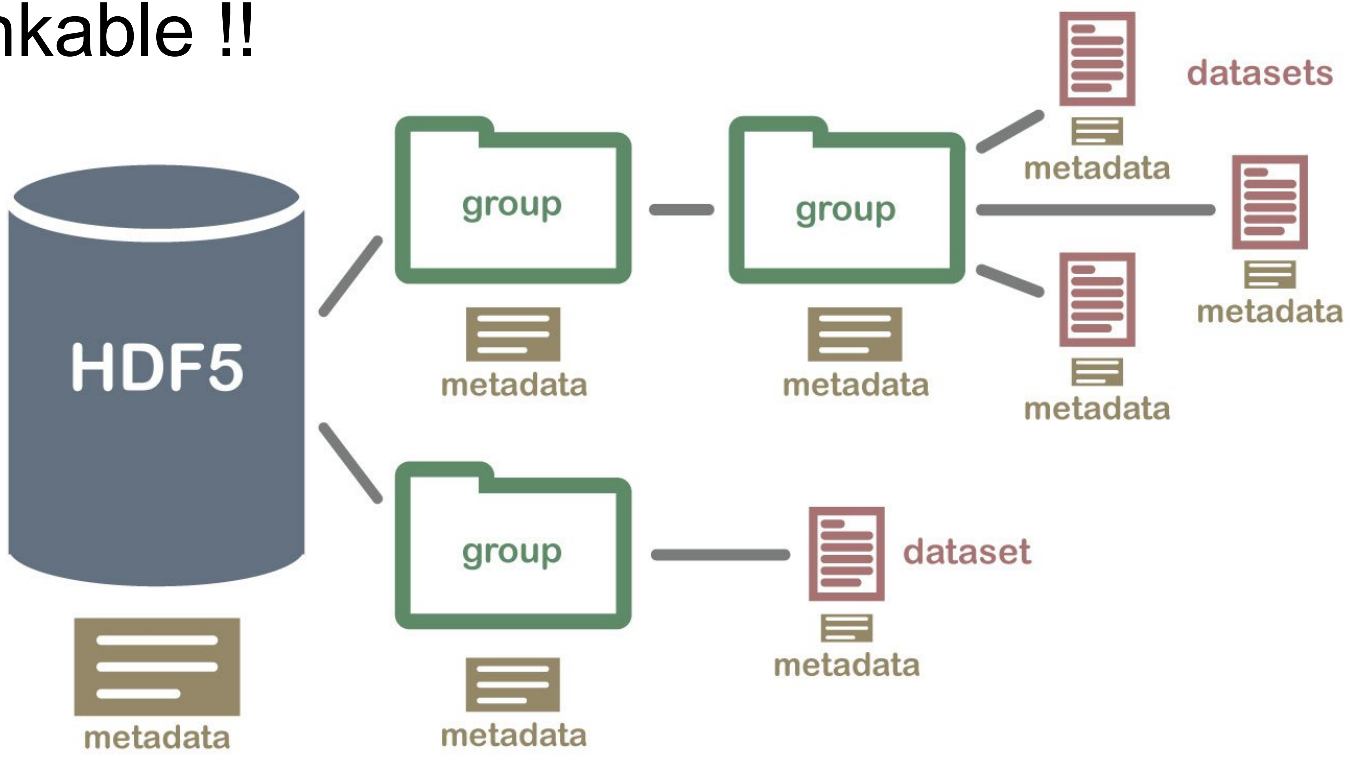
Iterable-style dataset
__iter__

Pipelined Access
to Object Store



Other Formats – HDF5

Chunkable !!



Other Formats – Parquet

Chunkable !!

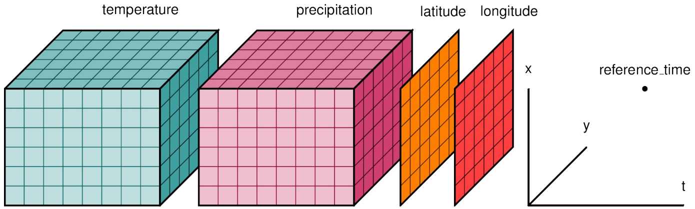
	Column 1	Column 2	Column 3	Column 4	Column 5
	Product	Customer	Country	Date	Sales Amount
Row Group 1	Ball	John Doe	USA	2023-01-01	100
	T-Shirt	John Doe	USA	2023-01-02	200
Row Group 2	Socks	Maria Adams	UK	2023-01-01	300
	Socks	Antonio Grant	USA	2023-01-03	100
Row Group 3	T-Shirt	Maria Adams	UK	2023-01-02	500
	Socks	John Doe	USA	2023-01-05	200

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

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!

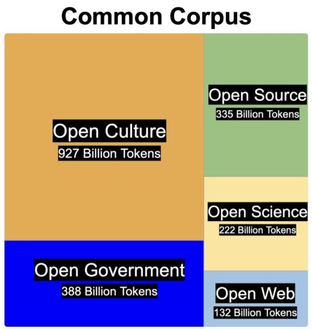
For Short Dataset:
Numpy/Pickle is the best suitable storage format !!

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

Case Study 1



- Large text corpus for LLM pretraining or SFT (RefinedWeb, ...)

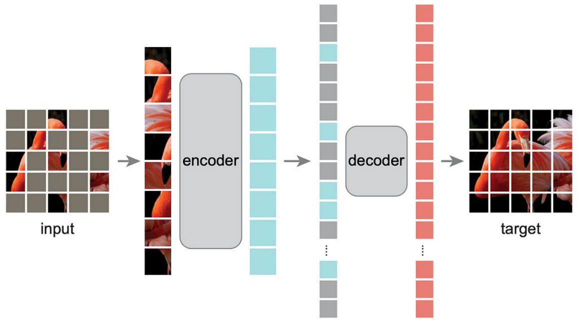
Performance of Dataloader ?

Shuffing and data balancing ?

Map-style or Iterable ?

Webdataset, Parquet, Zarr,... ?

Case Study 2



- Large Image Dataset for Auto-supervised Learning (Dino-v2, MAE...)

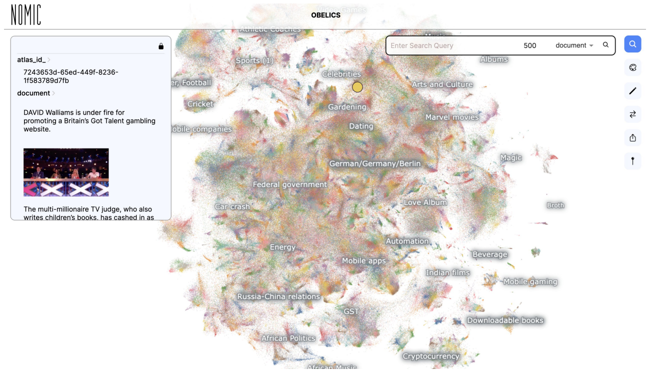
Performance of Dataloader ?

Shuffing and data balancing ?

Map-style or Iterable ?

Webdataset, Parquet, Zarr,... ?

Case Study 3



- Vision Language Model Pretraining Datasets (Obelics,...) ?

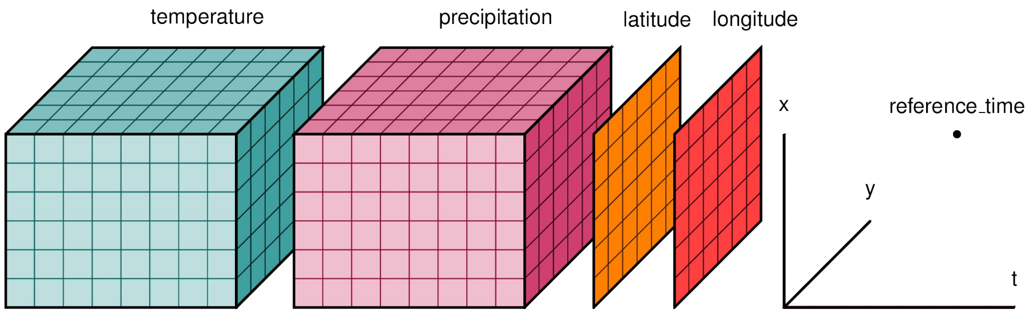
Performance of Dataloader ?

Shuffing and data balancing ?

Map-style or Iterable ?

Webdataset, Parquet, Zarr,... ?

Case Study 4



- Large Climatology Dataset ?

Performance of Dataloader ?

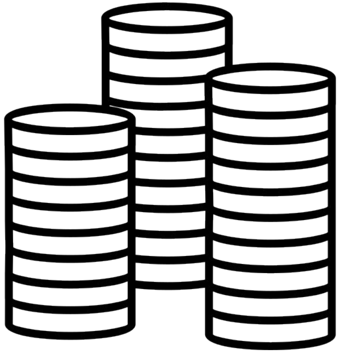
Shuffing and data balancing ?

Map-style or Iterable ?

Webdataset, Parquet, Zarr,... ?

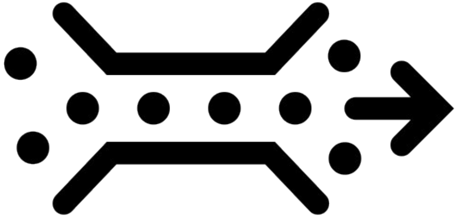
Conclusion

Storage Disks



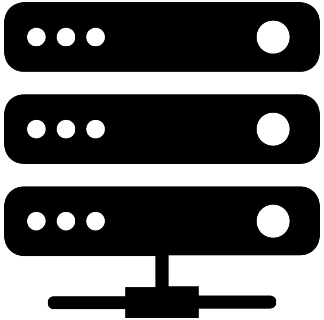
1. I/O performance

Interconnection Network
Omnipath



2. Shared Bandwidth

CPU workers



3. Decoder performance

- Disk spaces: WORK, DSDIR or SCRATCH ?
- Data format: binary or compressed ?
- Dataset format: adapted format ?