Quiver: An informed storage cache for Deep Learning

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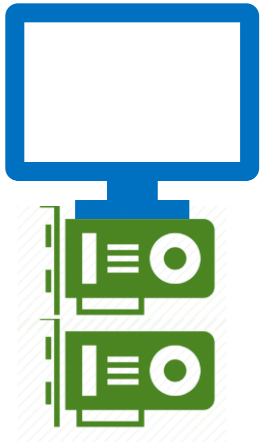
Deep Learning: Important systems workload

- Already powers many real-world applications
  - Voice assistants
  - Web search
- Compute intensive – expensive hardware e.g. GPUs



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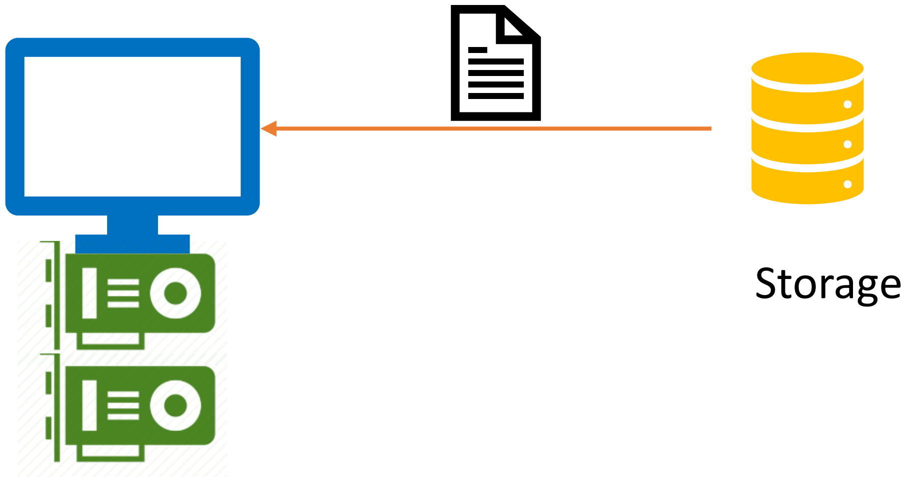

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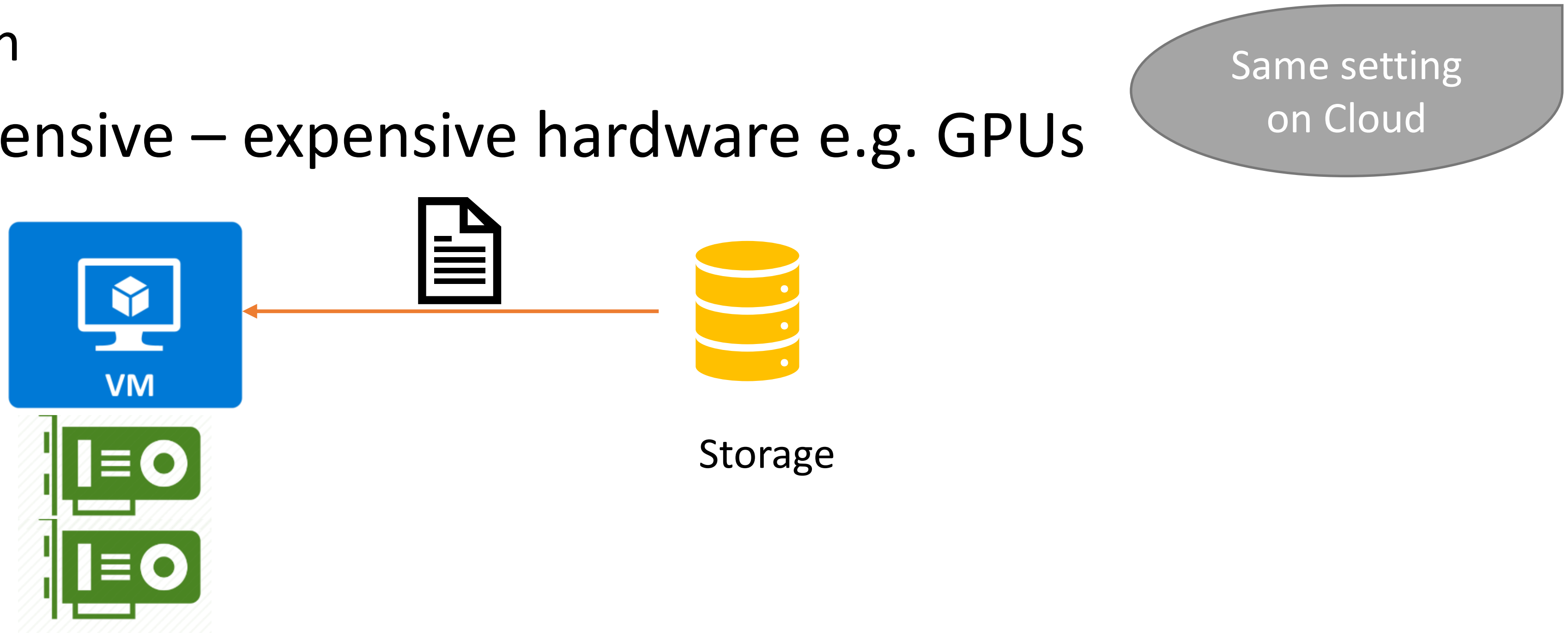

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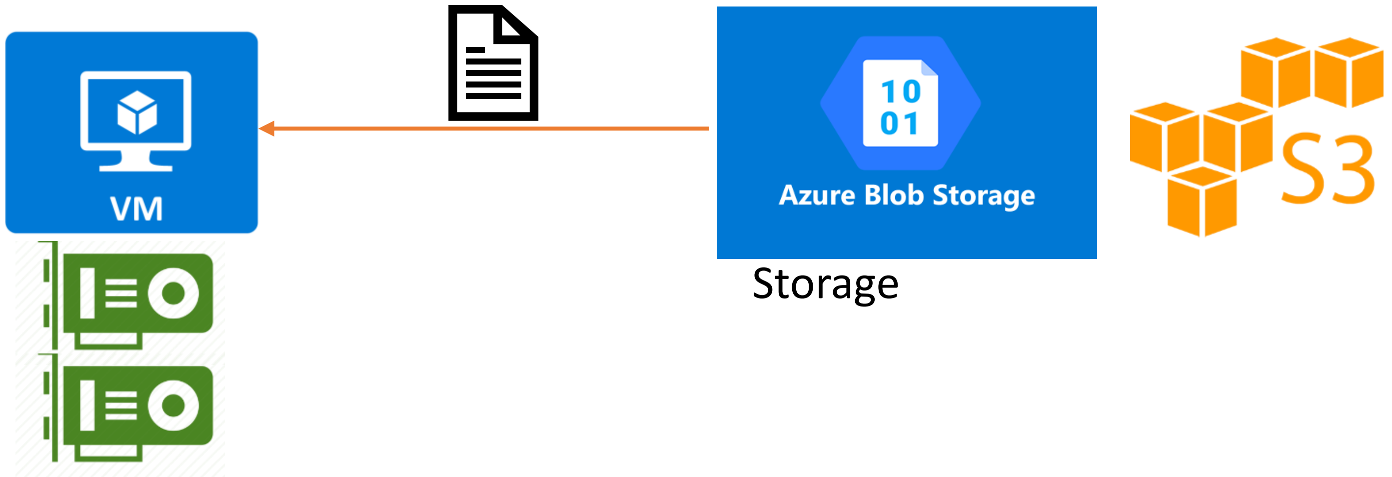

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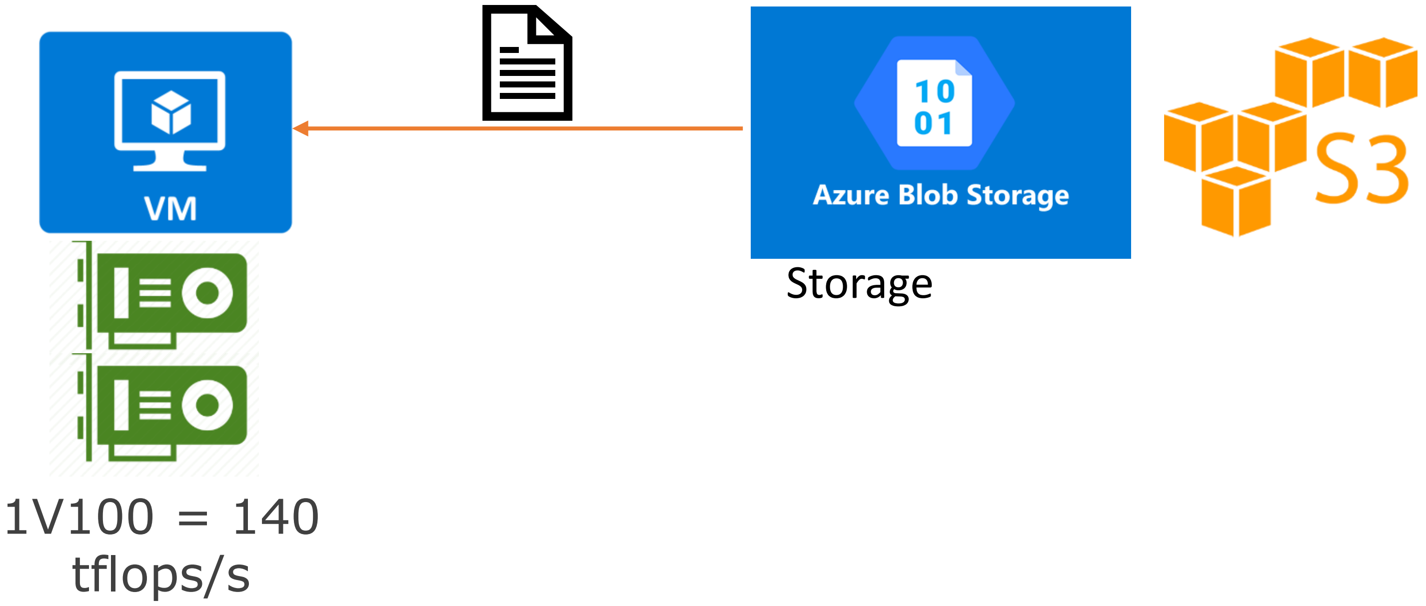
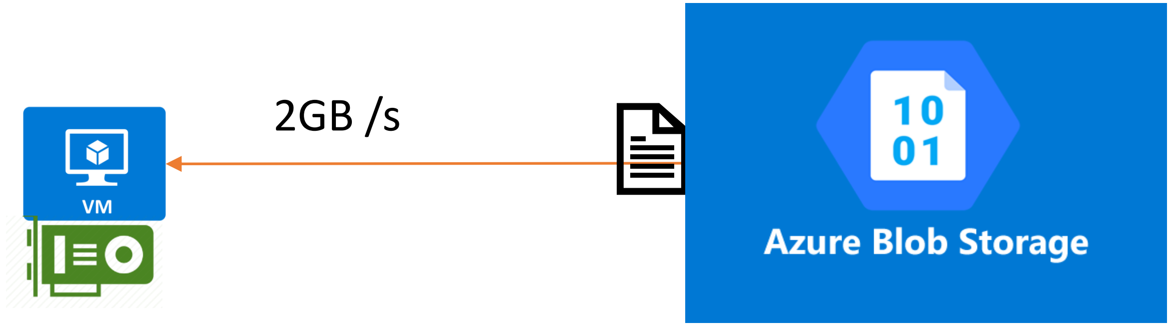


Example workload

- Resnet50 is a popular vision model
- Process 10,500 images/sec on 8 Nvidia V100s
- **Goal: Keep GPUs busy and utilize them efficiently**



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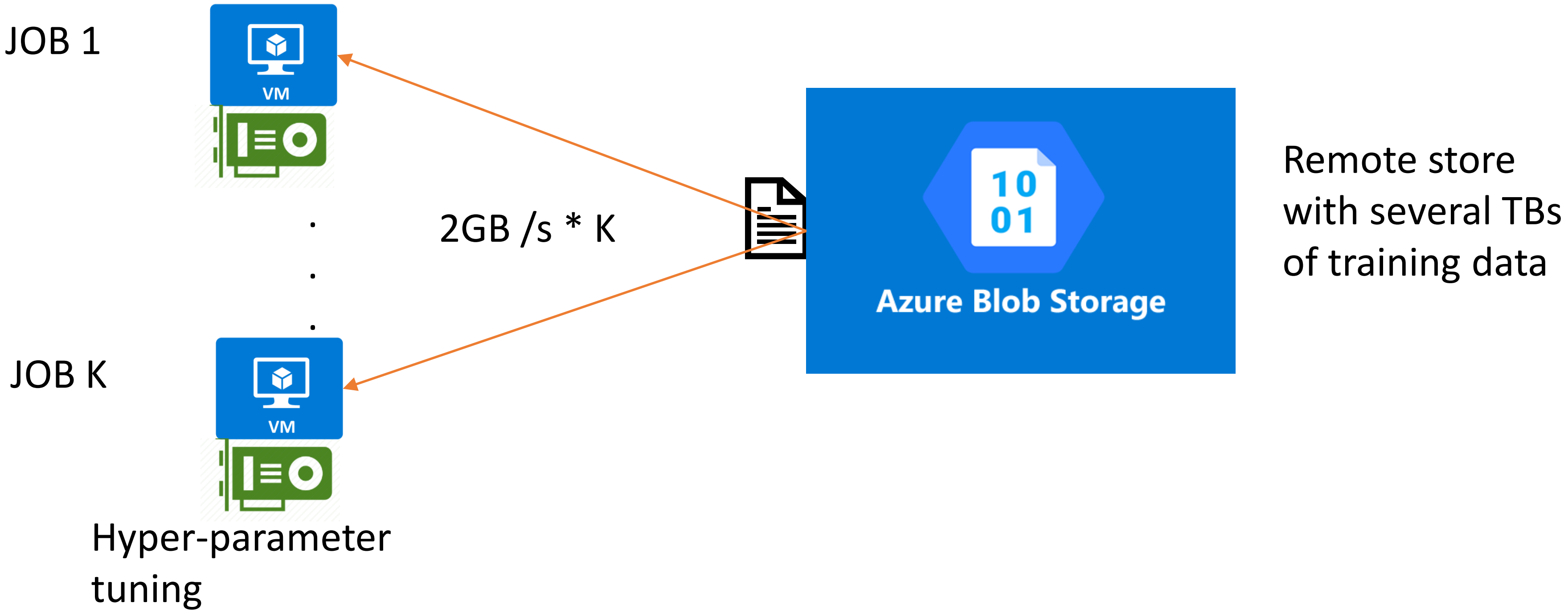

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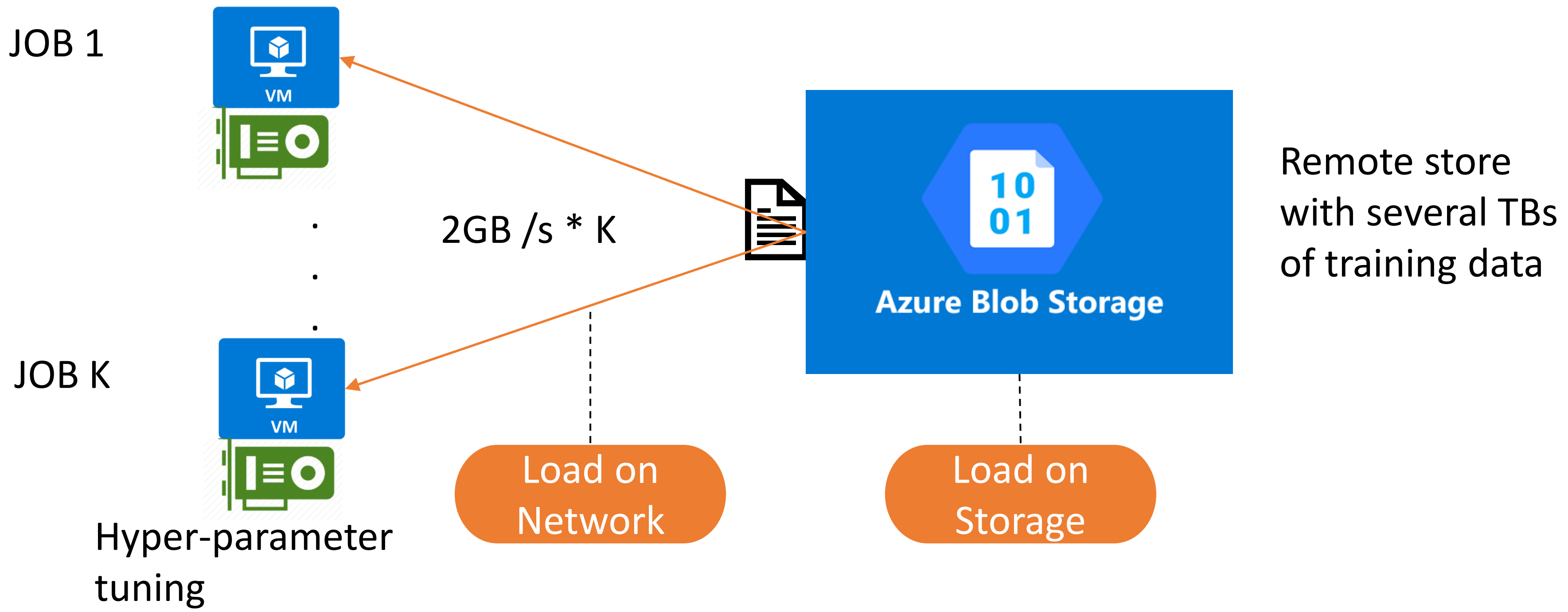

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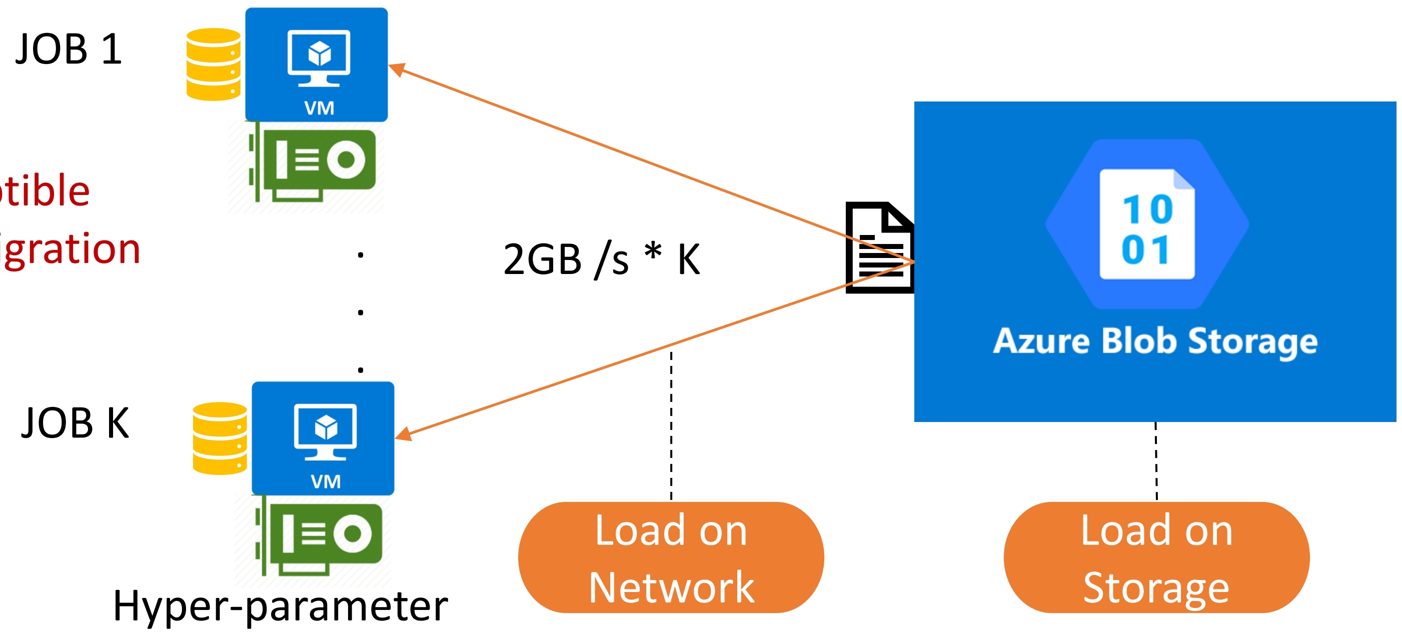
- Cheap Preemptible VMs => Job Migration
- Large datasets



Hyper-parameter tuning

Remote store with several TBs of training data

Quiver: Key ideas

- Domain specific intelligence at caching layer
  - Substitutability – Use existing contents of the cache to avoid thrashing
- Hash-based content addressing for security
- Co-designed with deep-learning framework (PyTorch)
- Dynamically manages cache allocation
- Improve cluster throughput up-to 2.3x

Structure

- Introduction & Motivation
- Background
- Design
- Implementation
- Evaluation

Background: Deep Learning

- Learn a model to **represent** training data
- Iterate over random subsets of input data – **Mini batch**
- Perform **Gradient Descent (SGD)** on each mini-batch
- Process the entire dataset in random order – **Epoch**

A cache for DLT jobs

- DLT datasets are accessed multiple times
  - Within same job: Multiple epochs read the entire dataset
  - Across jobs: Hyperparameter exploration, popular datasets (e.g. ImageNet)
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  - **Random access** within epoch => Partial caching can cause thrashing (e.g. LRU)
  - **Job Heterogeneity** => Not all jobs benefit the same from caching
  - **Secure inter-job data access**

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- **Quiver: Use domain intelligence to address these challenges**

#1: Thrashing-proof partial caching

- Two I/O properties
  - Each input touched once in an epoch
  - Every mini-batch needs to be randomly sampled

- **Substitutable hits**
  - I/O is substitutable
  - Mini-batch samples order does not matter, as long as it is random

#1: Thrashing-proof partial caching

- Substitutability while sampling
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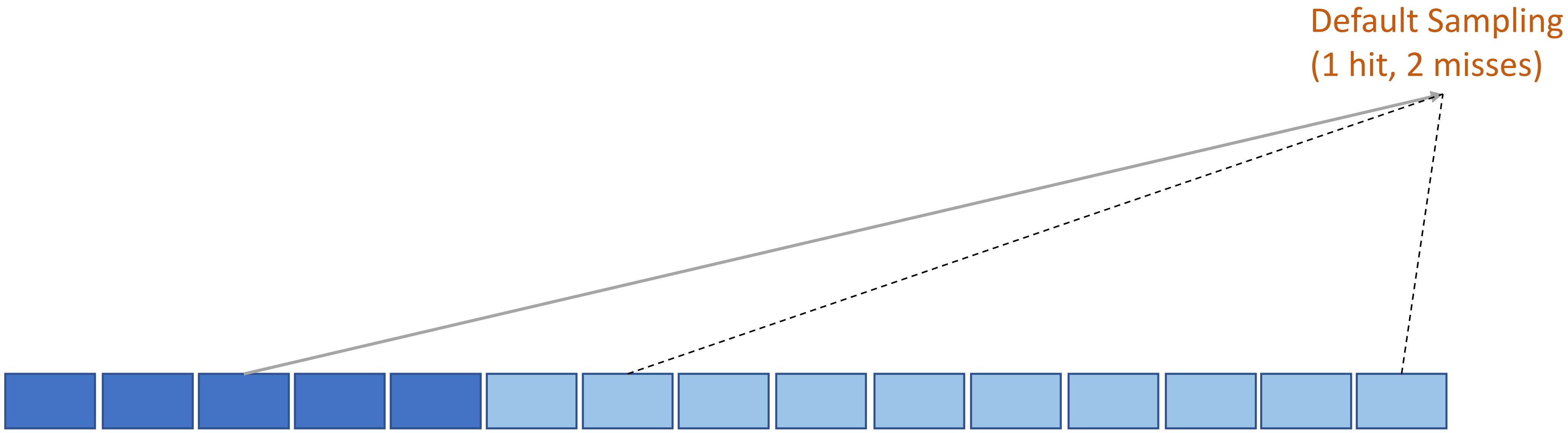

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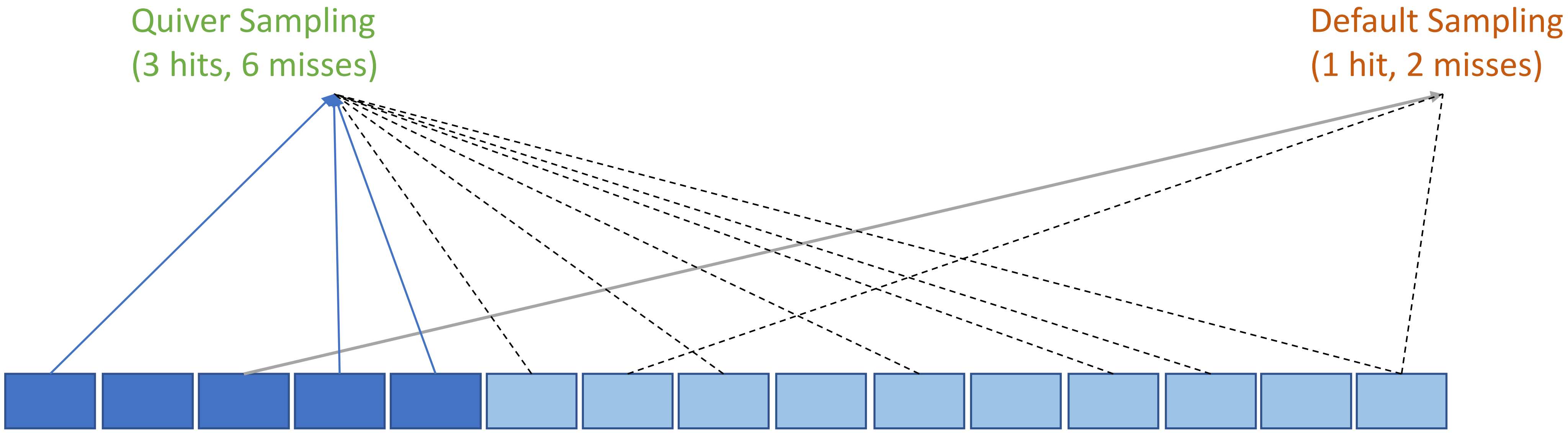

#2: Job heterogeneity and caching

- Benefit-aware caching to handle Job heterogeneity
  - Time per mini-batch is an application-specific metric for performance
    - Allows cheap profiling to measure benefits from cache
- **Predictability**
  - Measure time per minibatch with different caching modes
  - Given total space budget, the manager allocates cache per dataset

#3: Secure Inter-Job Data access

- Multiple jobs and users share cache
- Data needs reuse/sharing while retaining isolation
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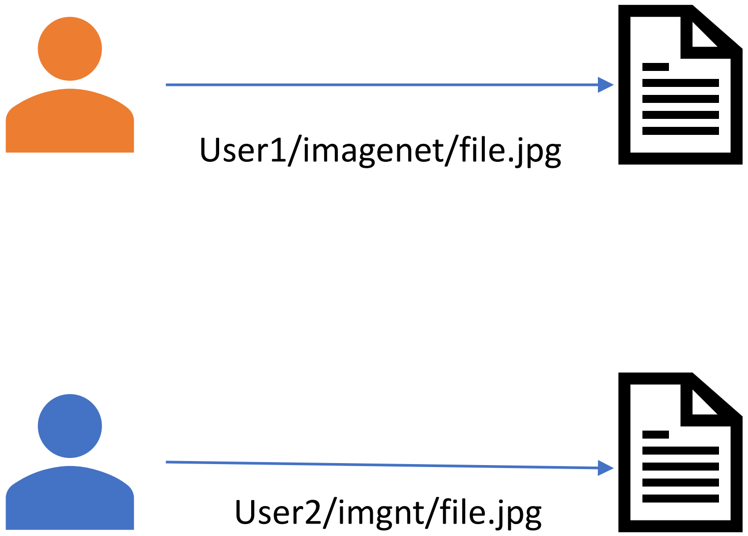

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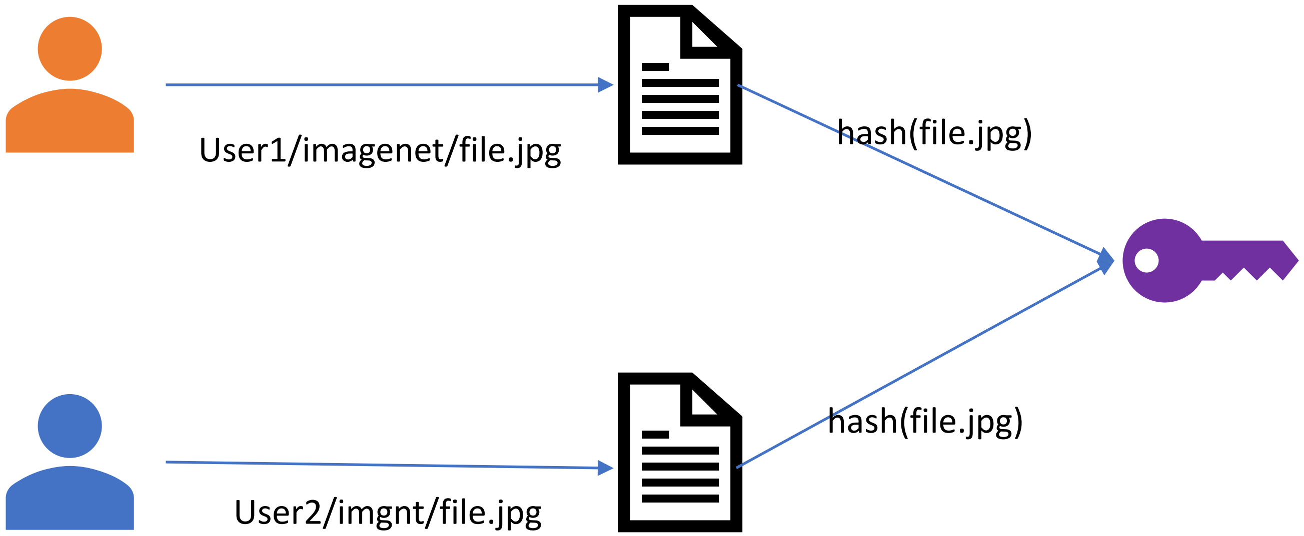

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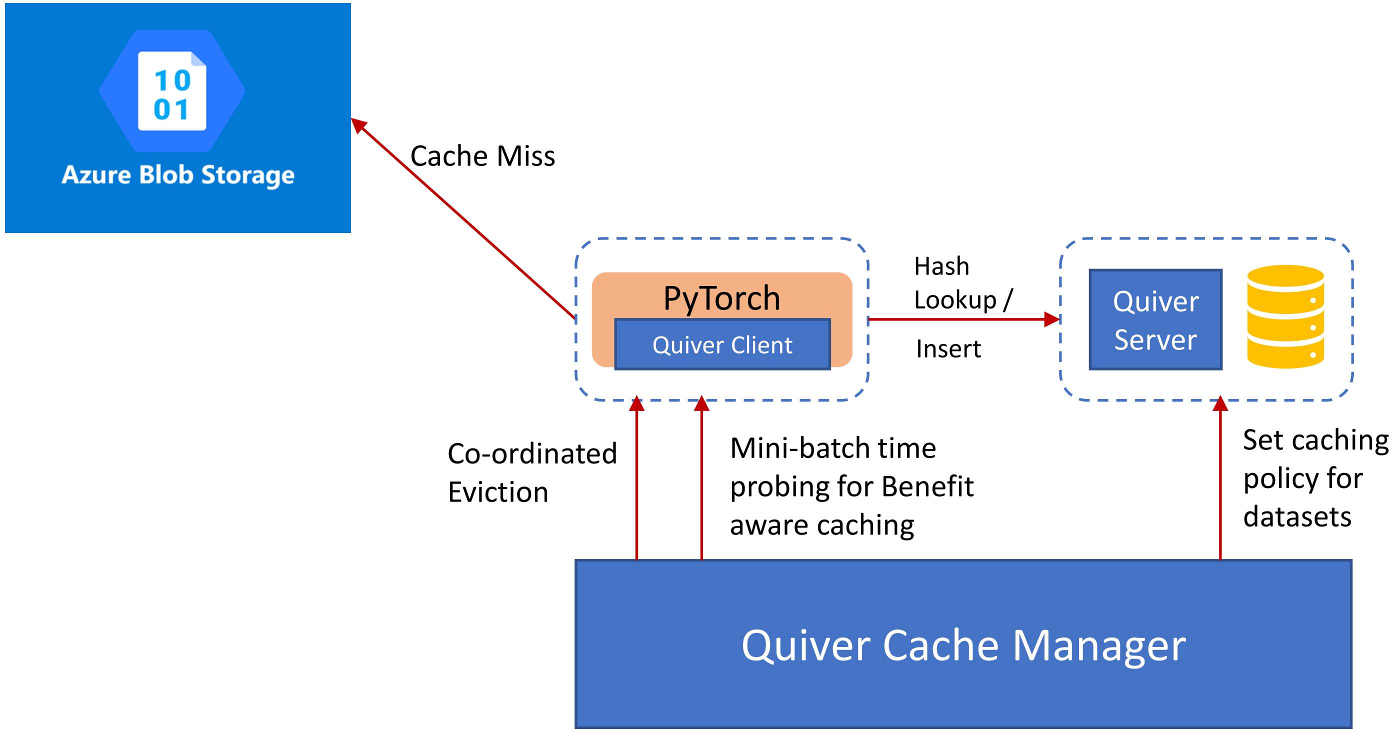
Architecture of Quiver

- Quiver cache server
- Quiver cache client co-designed with PyTorch
- Quiver cache manager
- Quiver instance types
    1. Entire cluster
    2. Each rack



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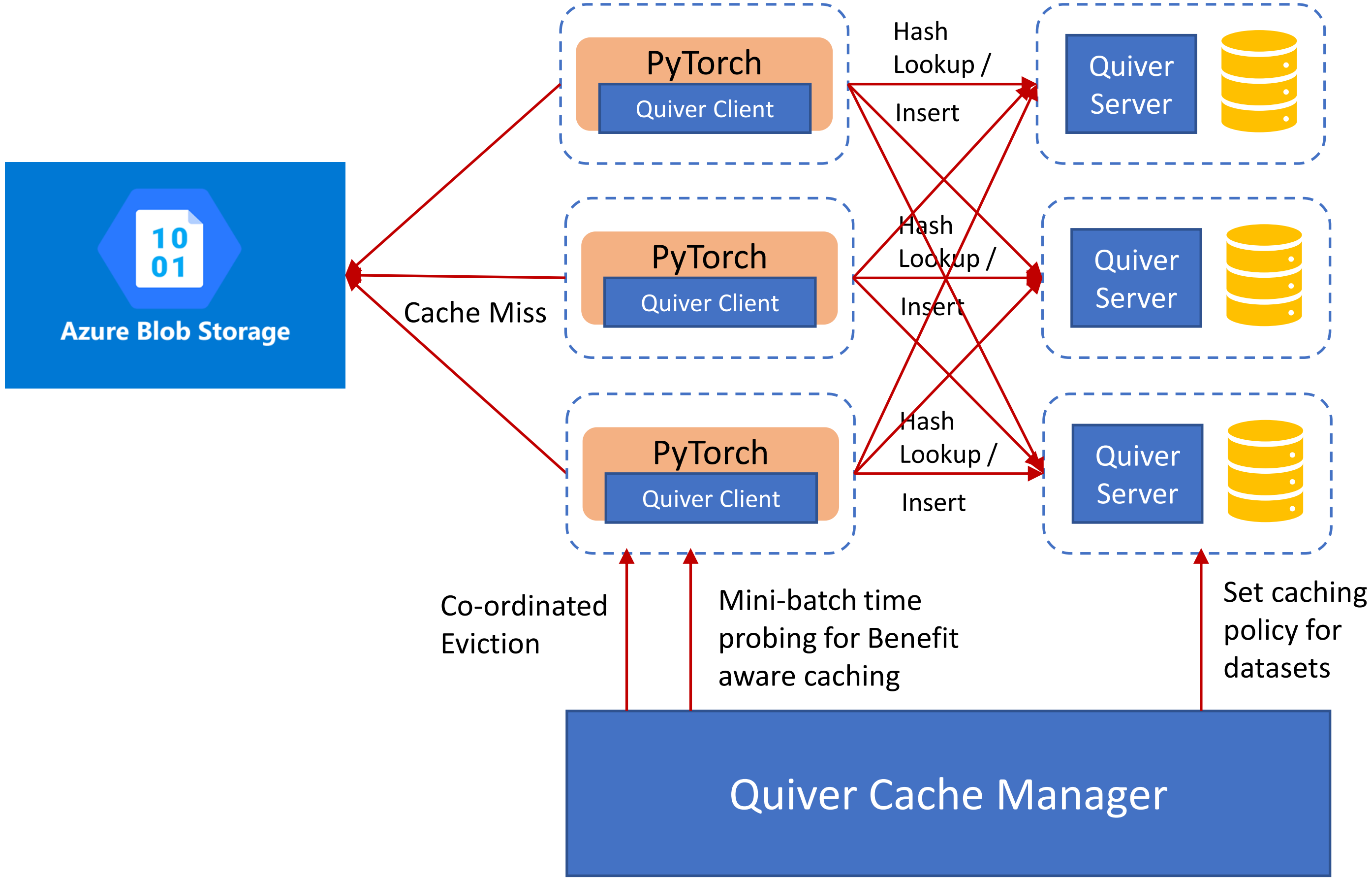

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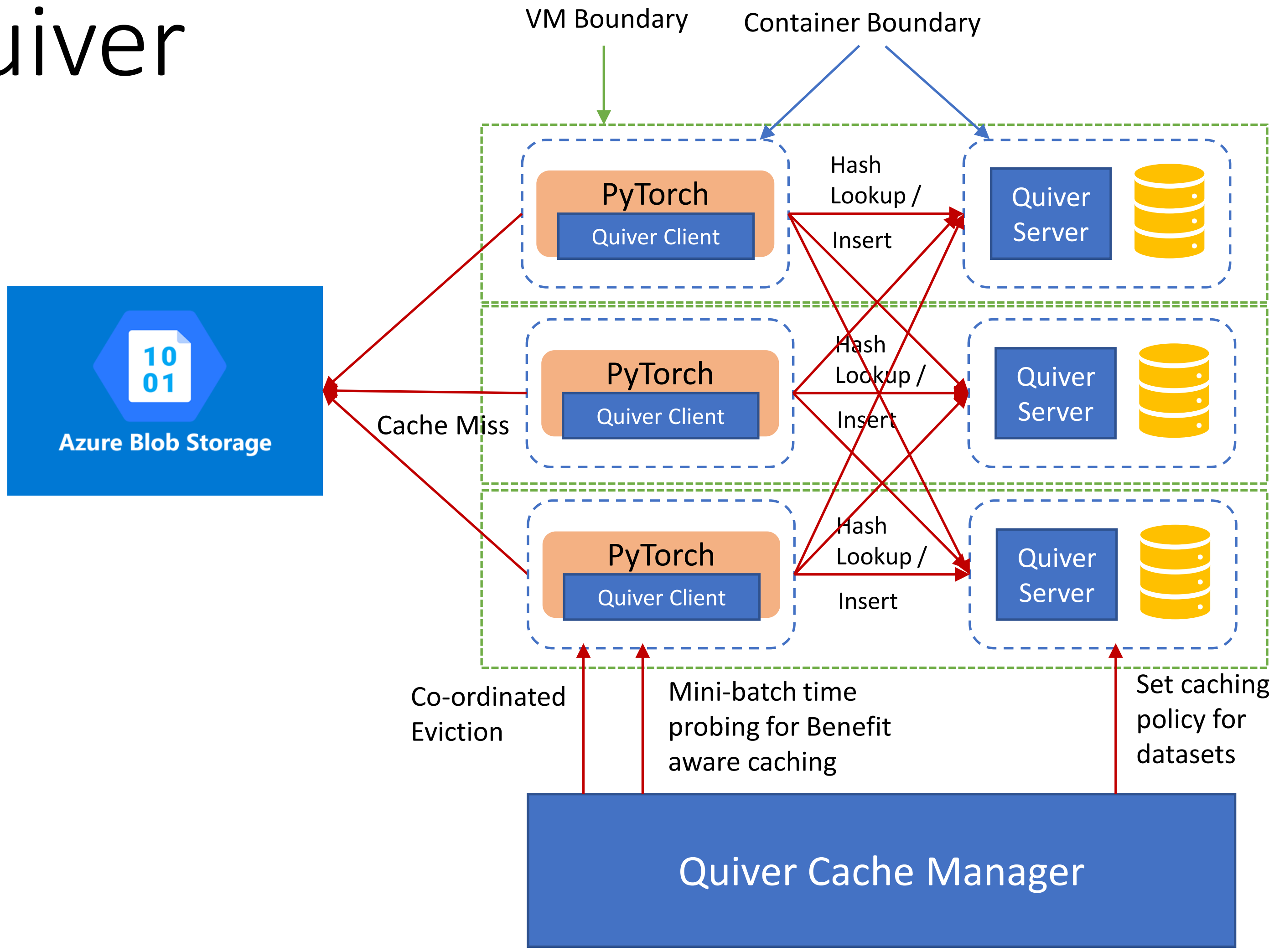

Cache Access

- Client is integrated with PyTorch data-layer
  - Fetches files from remote on misses
  - Populates the cache servers
- Works with **hash-digest** file
- Incorporates ***substitutable hits*** and ***co-operative*** **miss handling**

Hash digest and Partition

- Dataset is represented by a hash-digest
- Major components of an entry in the hash-file
  - <content_hash: file_location>
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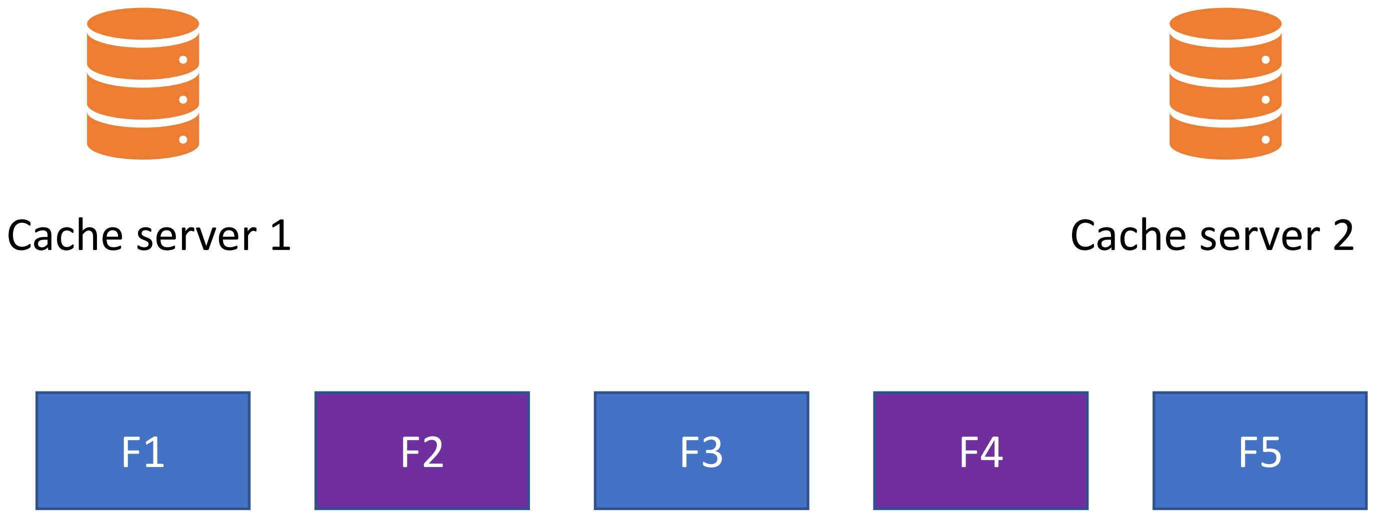

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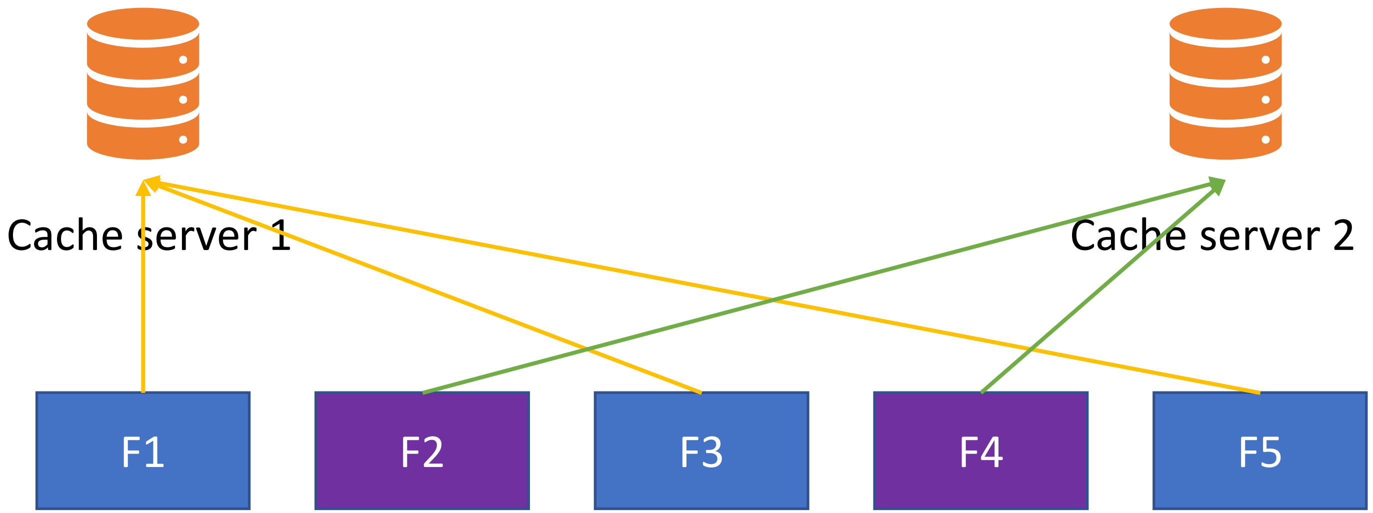

Co-operative miss handling

- Misses are sharded across jobs using same dataset.
  - Sharding is implicit by randomizing indices
  - *Happens naturally in DLT access pattern*
  - *Jobs benefit from other jobs as they progress*

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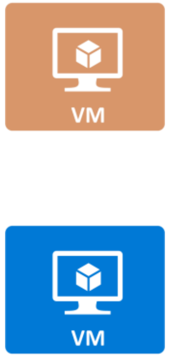

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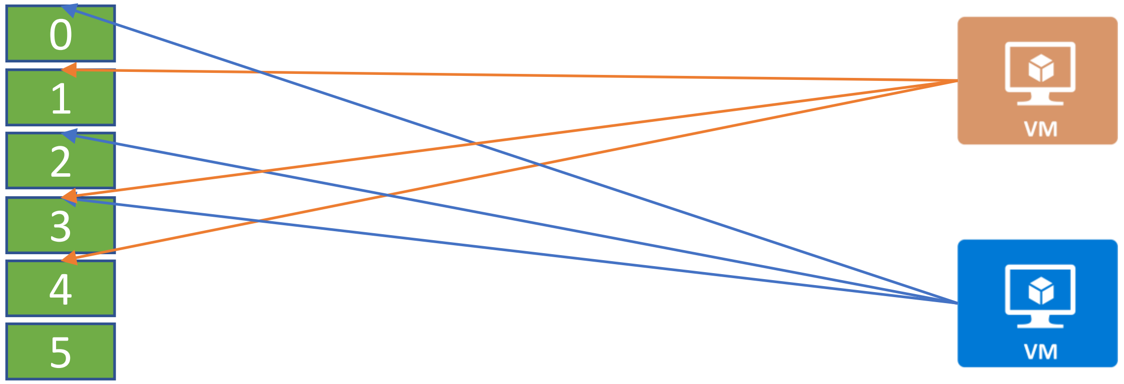
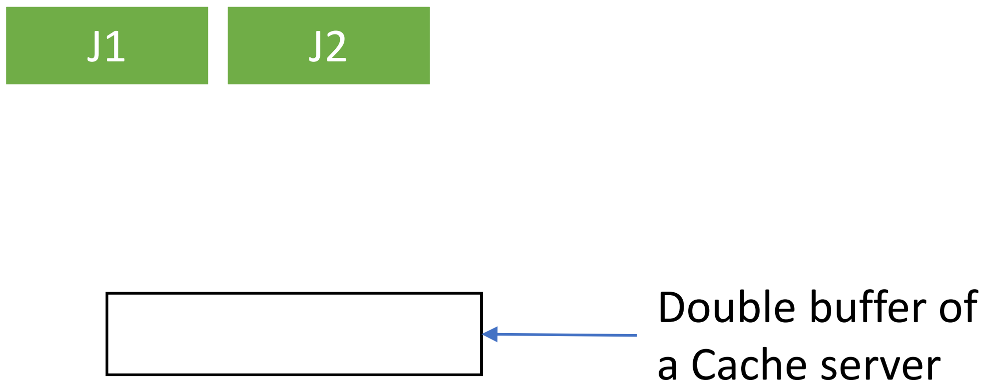


Co-ordinated eviction

- Dataset partition
  - Digest file is partitioned into given number of chunks
- Double buffering of chunks
  - Chunks allow coordinated access of cache
  - Co-ordinated eviction
    - Mark for eviction – no new refs
    - Then evict
    - Similar to UNIX **unlink** call



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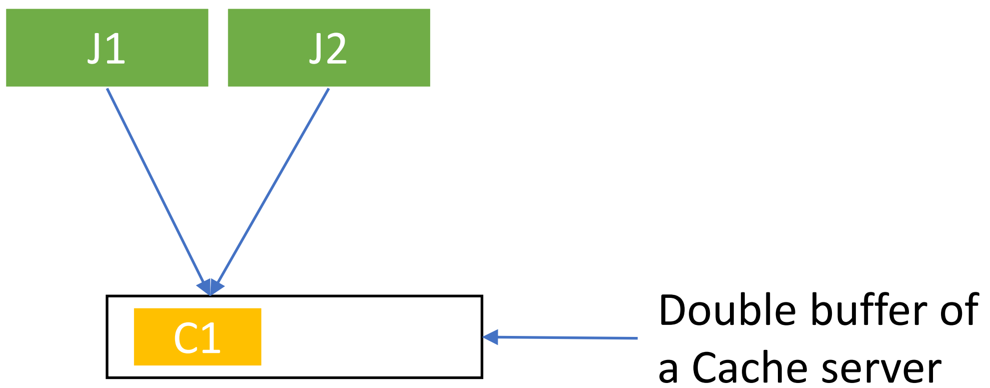

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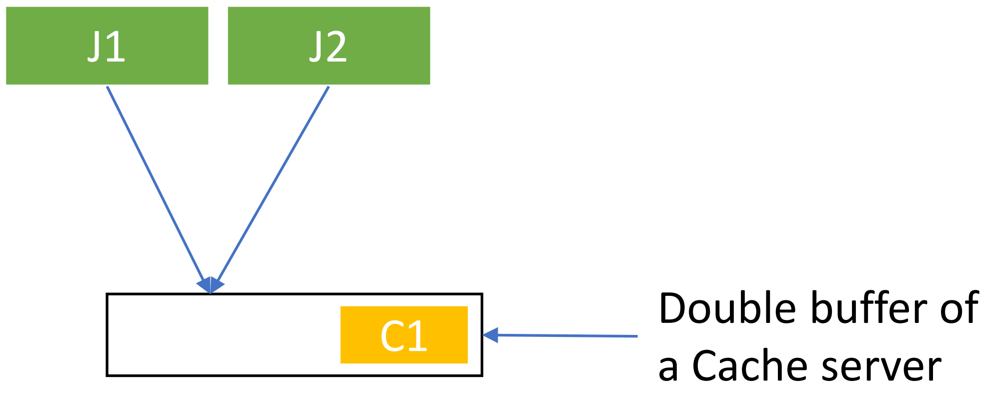

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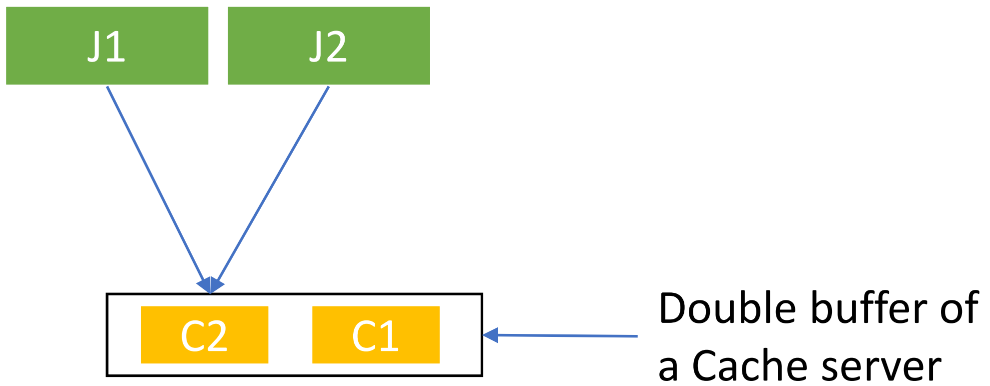

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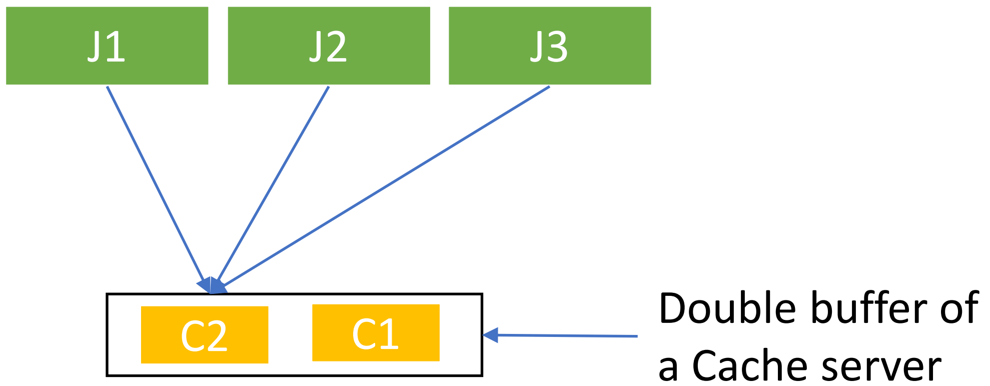

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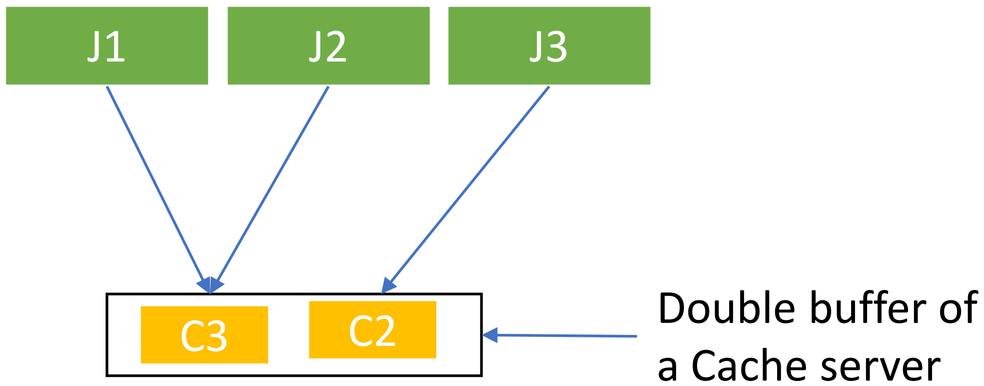

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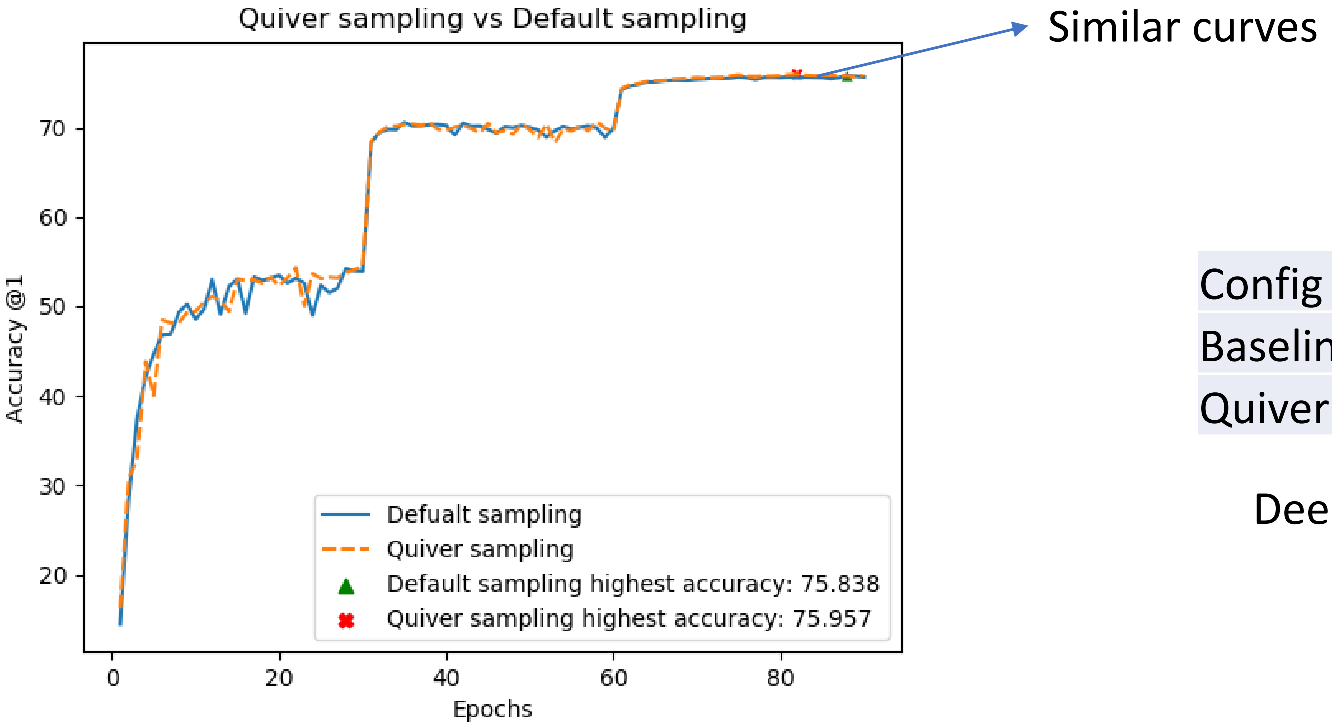
Implementation

- Cache client (900 LoC)
  - Dataloader of PyTorch (v 1.1.0)
  - Dataset of PyTorch
  - Sampler of PyTorch
- Cache server (1200 LOC)
  - A C++ key value store
- Cache manager
  - A python program

Evaluation Setup

- Cluster (48 GPUs)
    - 6 VMs with 4 NVIDIA P100 GPUs
    - 6 VMs with 4 NVIDIA P40 GPUs
- Workloads
    - Resnet50 on Imagenet dataset (154 GB)
    - Inception_V3 on openimages dataset (531 GB)
    - DeepSpeech2 on LibriSpeech dataset (90 GB)

Impact on accuracy

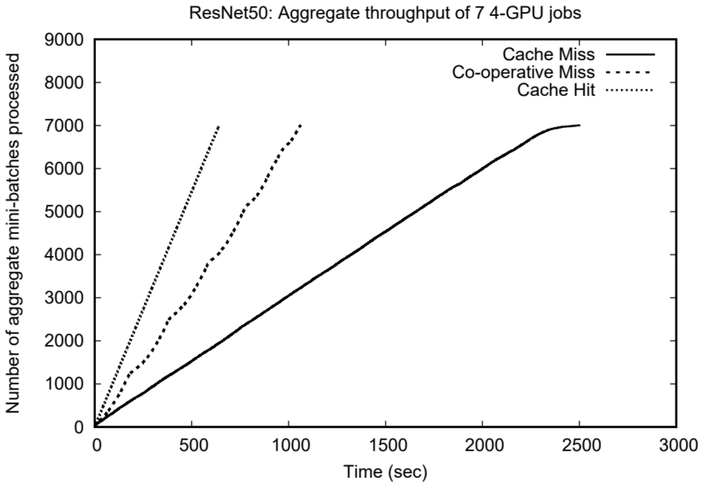


RESNET50 on Imagenet

Config	Word Error Rate (WER)
Baseline Sampling	22.29
Quiver Sampling	22.32

DeepSpeech2 on LibriSpeech

Throughput increase because of quvier



Resnet50

Workload	Time for 7000 mini-batches (s)		
	Baseline	HIT	CO-OP
Resnet50	2505	646 (3.88x)	1064 (2.35x)

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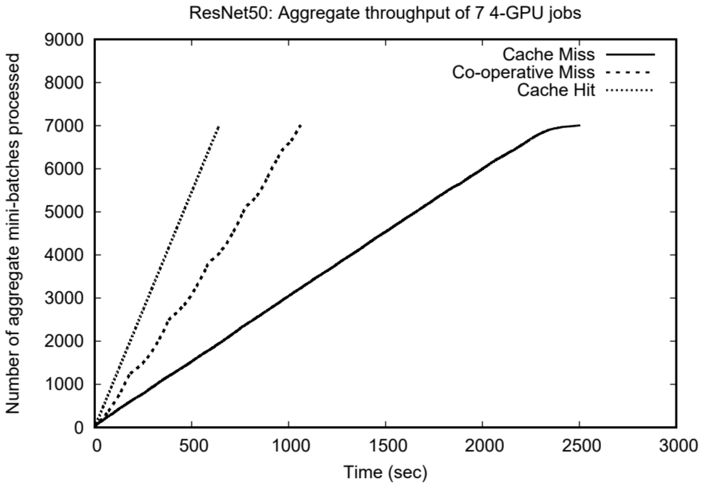
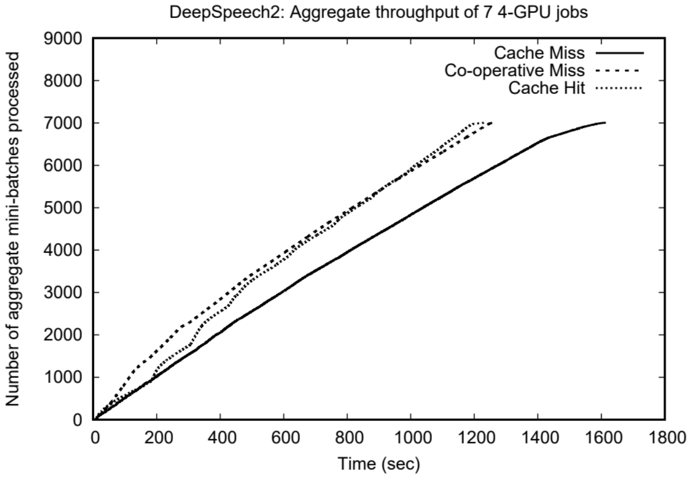


Resnet50

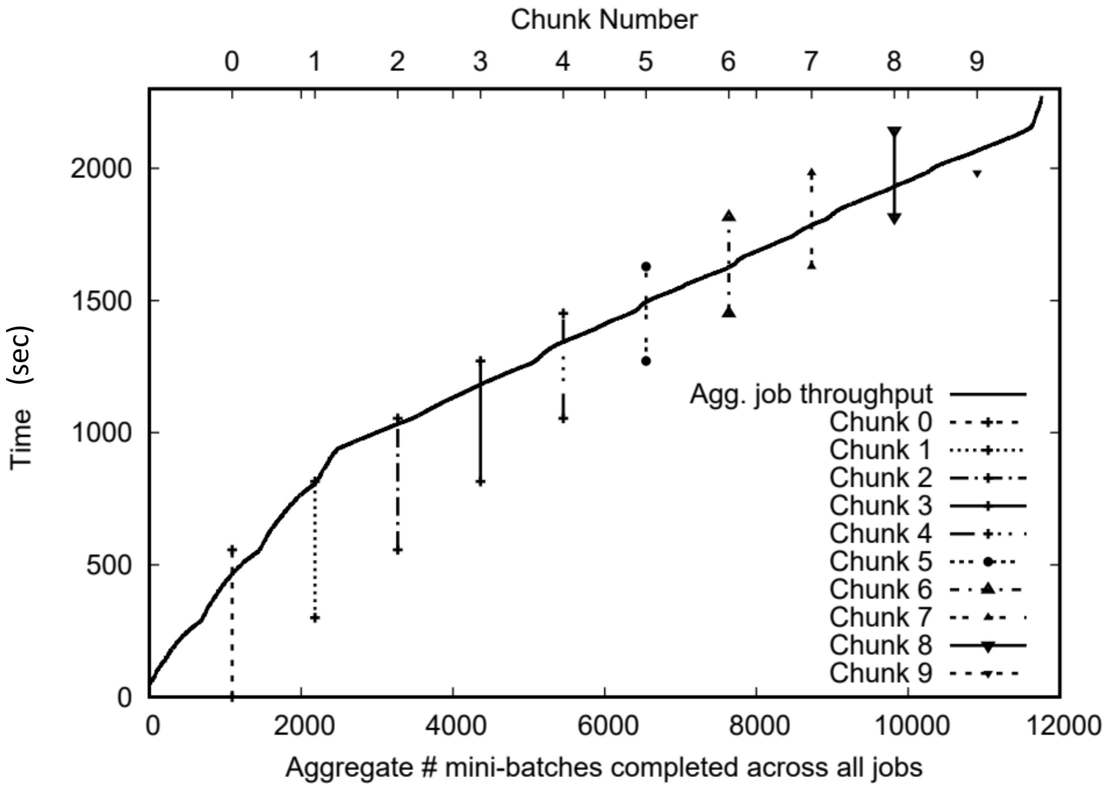
InceptionV3



DeepSpeech2

Workload	Time for 7000 mini-batches (s)		
	Baseline	HIT	CO-OP
Resnet50	2505	646 (3.88x)	1064 (2.35x)
Inception	2874	1274 (2.26x)	1817 (1.58x)
DeepSpeech	1614	1234 (1.31x)	1265 (1.28x)

Co-ordinated eviction in action



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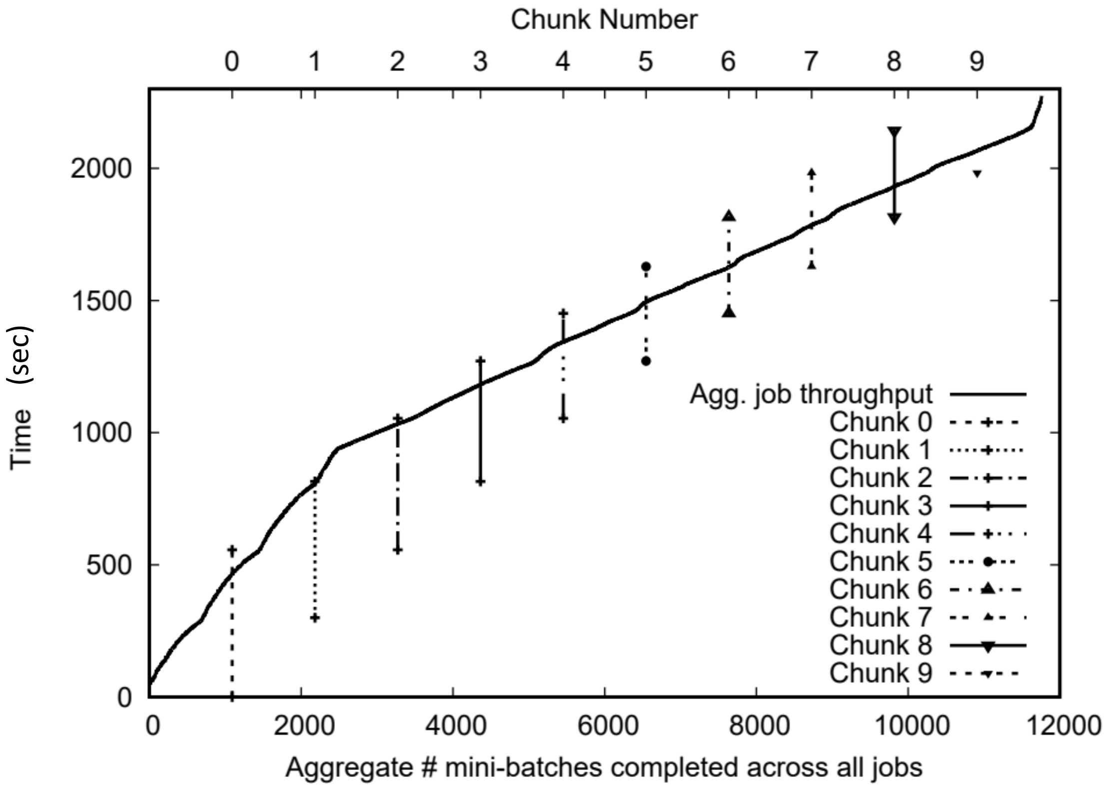

- 2 Chunks cached at a time
- New jobs start using 3rd chunk

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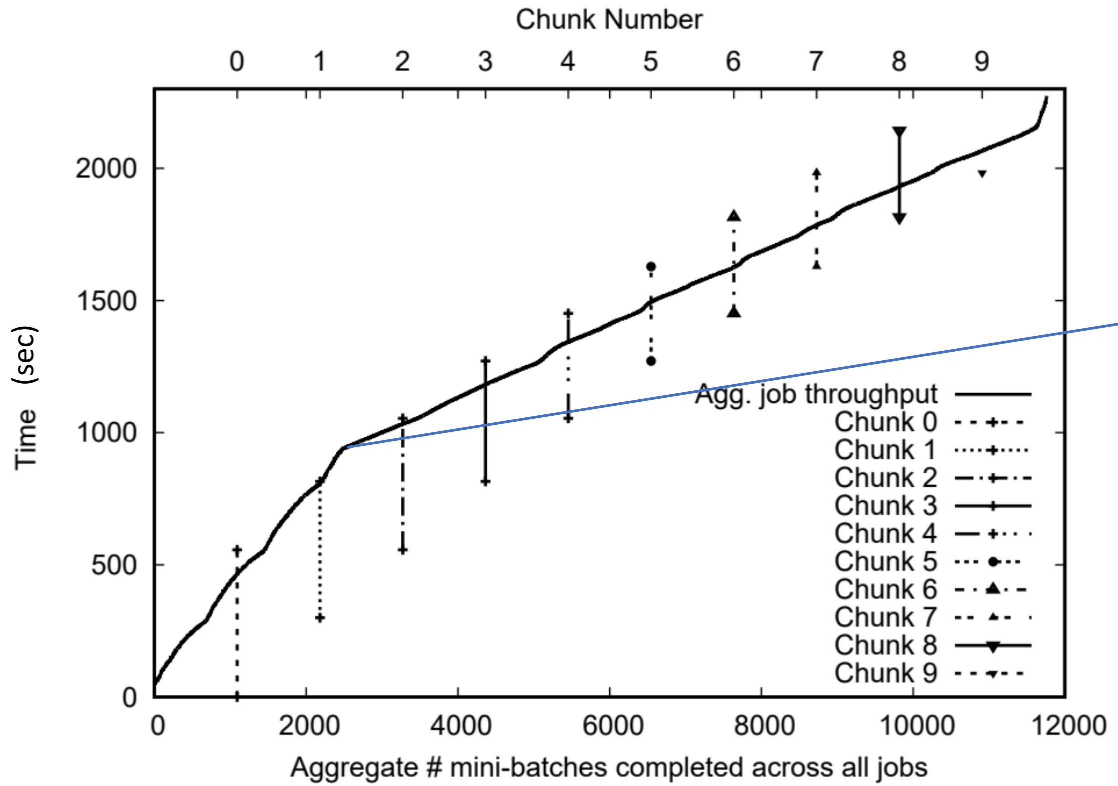

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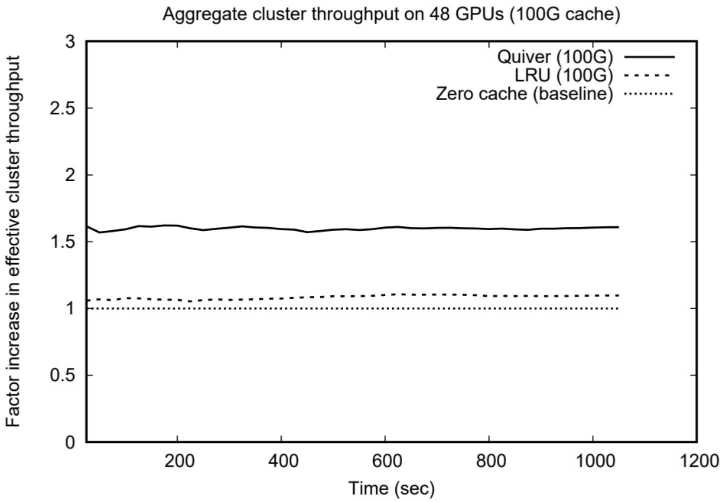
Benefit aware caching



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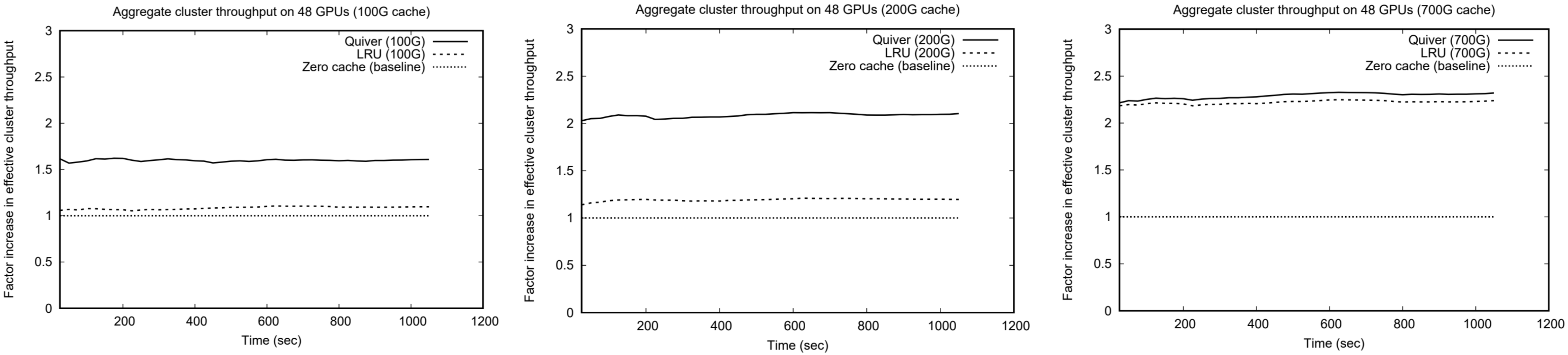

- Mixed workload – 12 Different jobs
- Quiver preferentially allocates cache to different datasets
- Quiver yields sizeable benefits even with tiny cache (100G)
- Improvement in cluster throughput ranges between 1.6x to 2.3x

Summary

- Quiver is a domain-specific storage cache for DLT jobs
- Utilizes I/O behavior of deep learning training jobs
  - Substitutable hits => New thrash-proof partial caching
  - Predictability => Benefit-aware caching

- Improves cluster GPU utilization by reducing I/O wait time
- Implemented in PyTorch