iCACHE: An Importance-Sampling-Informed Cache for Accelerating I/O-Bound DNN Model Training

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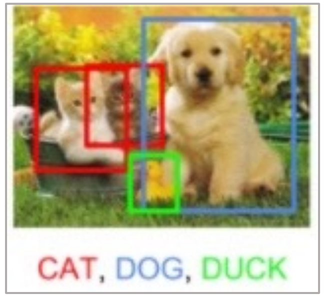
Deep Neural Network (DNN) Training

- DNN has been applied in a range of fields



- DNN training pipeline

Data Loading → 1st epoch: batch 1, batch 2, … … ; 2ed epoch: … … → Data Preprocessing → Forward and Backward Computation

Deep Neural Network (DNN) Training

➢ Characteristics of each stage

Data Loading

- **Poor temporal locality.** (Access each data item only once in each epoch)
- **Poor spatial locality.** (Fully random access)

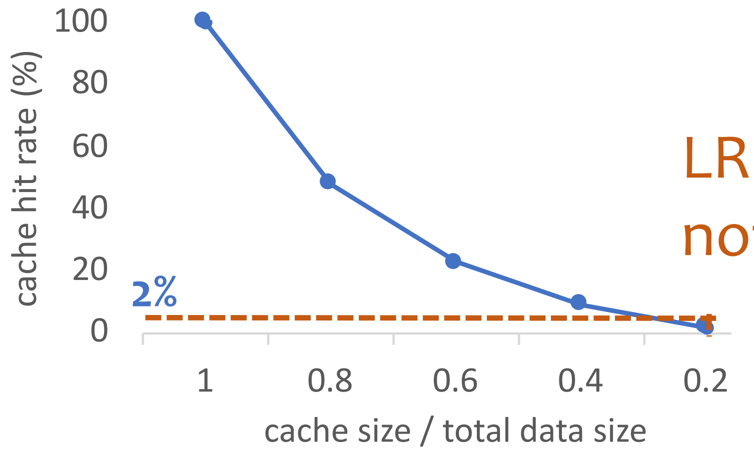
Data Preprocessing

- Operators are **usually lightweight**

Forward and Backward Computation

- DL accelerators are **getting faster**: GPU V100, A100, TPU, ASIC···

➢ When memory is insufficient for growing dataset



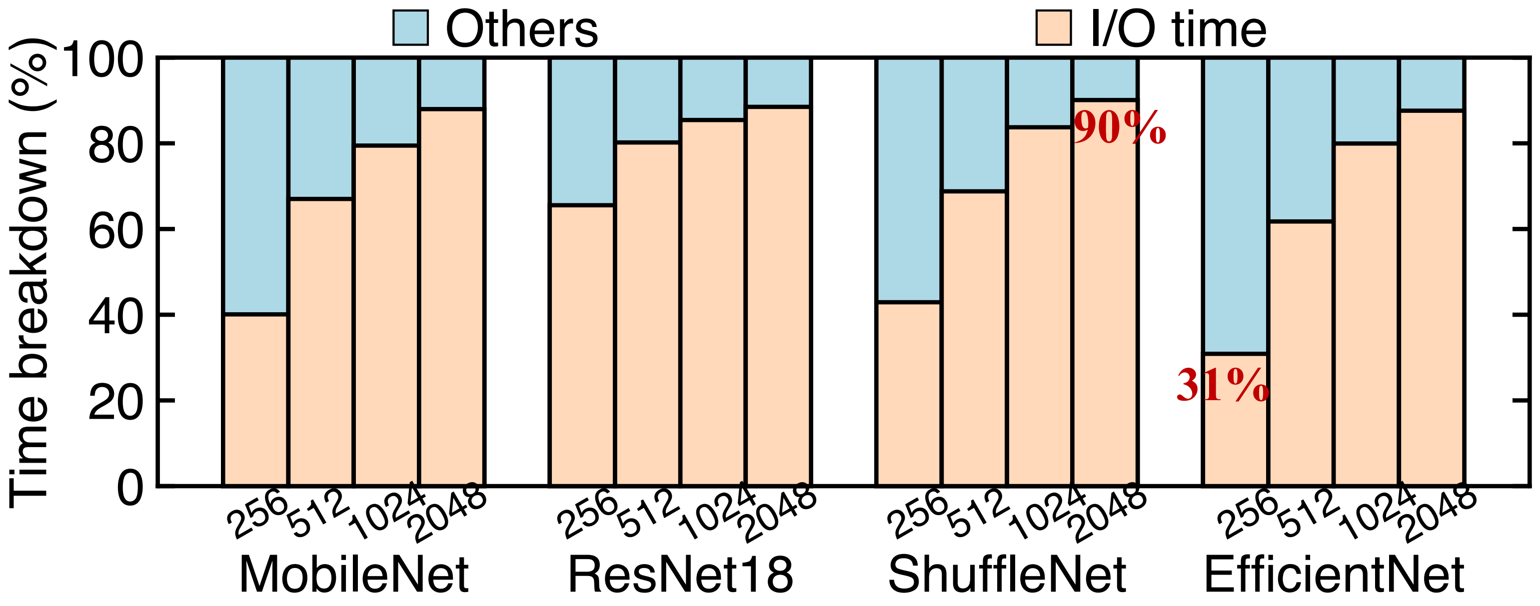
LRU-based cache is not practice.

Data Loading is becoming the training bottleneck ! ☹

Deep Neural Network (DNN) Training

➢ Common techniques to accelerate DNN training

- Data prefetching
- Traditional data caching
- Batch size adjustment
- Multi-GPU training



These widely used techniques are inefficient for I/O-bound DNN tasks.

Related Work: DNN Cache Optimization

- **Explore data locality in more depth.**
  - between **epochs** → CoorDL [VLDB' 21]: A static cache.
  - between **multiple jobs** → OneAccess [HotCloud' 19], et al.: Sharing cached data.

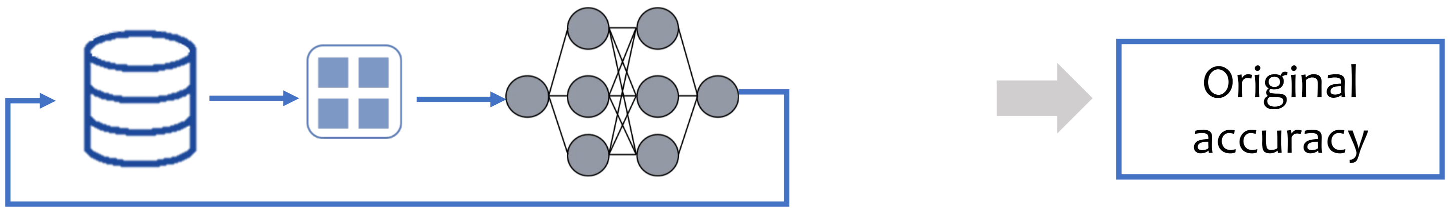
- **Exploit data substitutability of DNN training.**
  - DeepIO [MASCOTS' 18], Quiver[FAST' 19]: Replace cache missed data with data in the cache

These techniques are not sufficient when data size is huge.
DNN applications in all of these work need to
fetch all data from cache/storage for each epoch training.

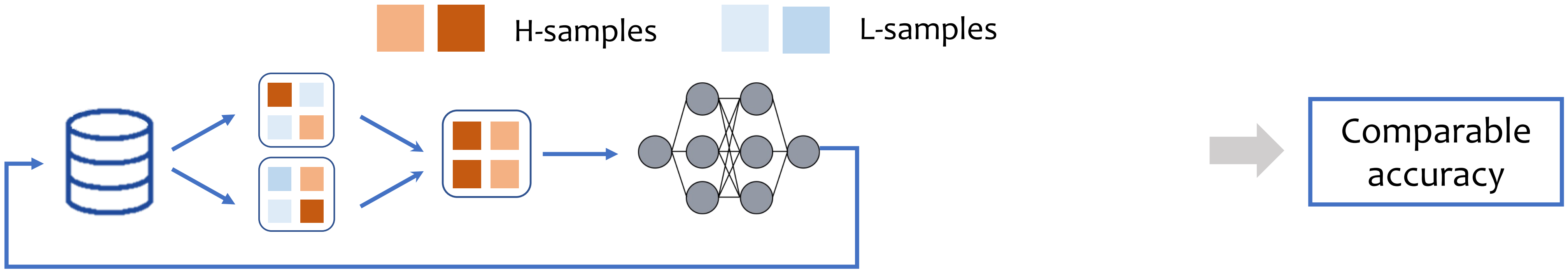
Opportunity from Importance Sampling

➢ For each epoch training:

a. Default DNN training:

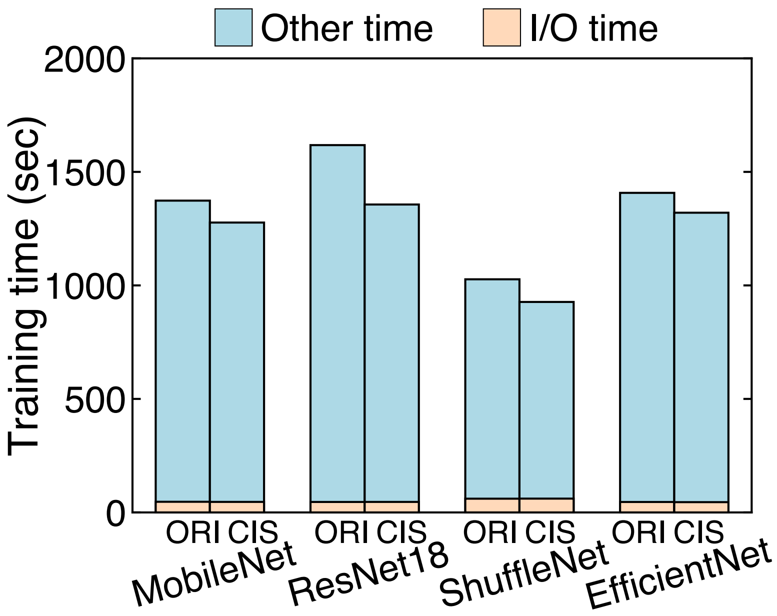


b. Importance sampling-based DNN training:

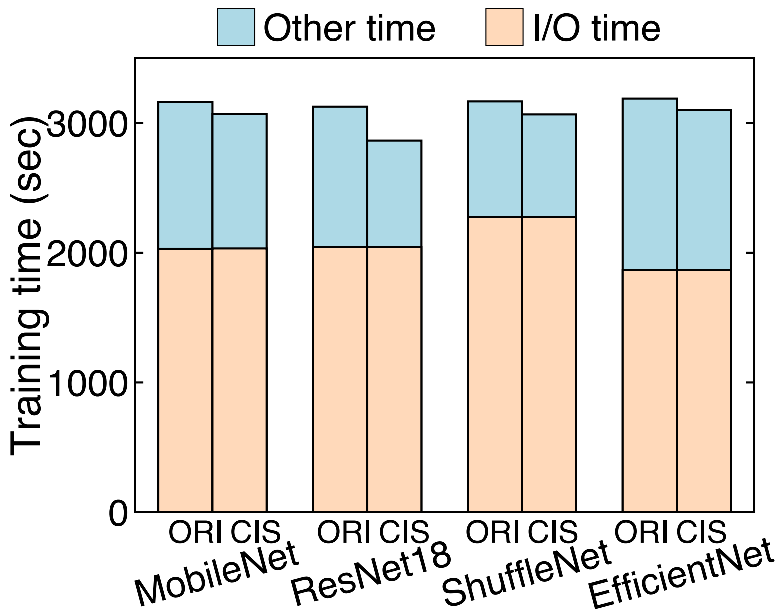


Opportunity from Importance Sampling

- ➢However, existing IS algorithms are designed for computing-bound tasks (We name them CIS).



a. Computing-bound training (cache size 100%)



b. I/O-bound training (cache size 20%)

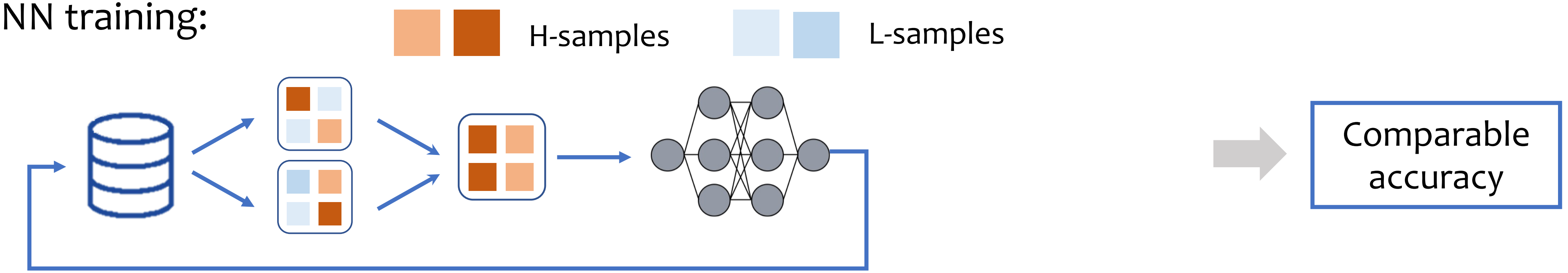
CIS Speed up training 1.3x ☺

CIS Speed up training 1.02x ☹

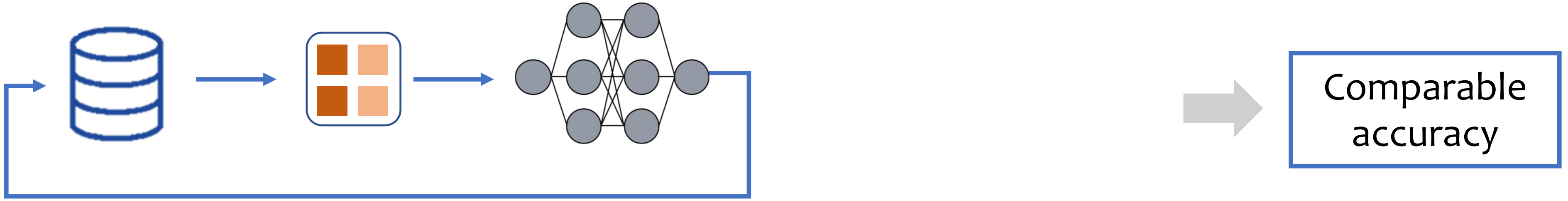
I/O-oriented Importance Sampling Algorithm

- Inspired by CIS, we propose I/O-oriented importance sampling (IIS).

b. CIS DNN training:



c. IIS DNN training:



The necessity of re-design cache optimization

➢ **It seems promising to combine IIS and cache optimization…**

IIS	→	Reduce **# of data items loaded**	Mitigate I/O bottleneck of DNN training
+			
Cache optimization	→	Reduce data loaded **from storage**	

IIS	select data items based on their **impact on model accuracy**
OS cache Quiver CoorDL… **Existing DNN cache system**	cache replacement based on **locality**

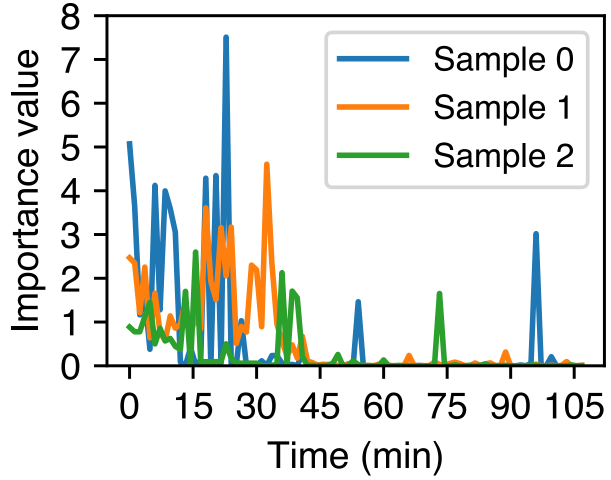
Unmatched

It is necessary to re-design cache management considering importance sampling.

Challenges

➢ **Intuitively, caching H-samples as many as possible. However…**

1. Importance value of a specific data item fluctuates during training.



❓ How to keep a maximum number of H-samples in the cache when the importance values changes to achieve high cache hit rate ?

2. Cache capacity is limited and L-samples are likely to be cache missed.

❓ How to deal with poor I/O efficiency when accessing L-samples ?

3. Cache misses caused by no job coordination.

❓ How to coordinate samples cached between multiple jobs ?

Outline

- Background & Motivation
- Design of iCACHE: an cache system to accelerate DNN training
- Implementation & Evaluation
- Summary & Conclusion

iCACHE Architecture

Cache clients

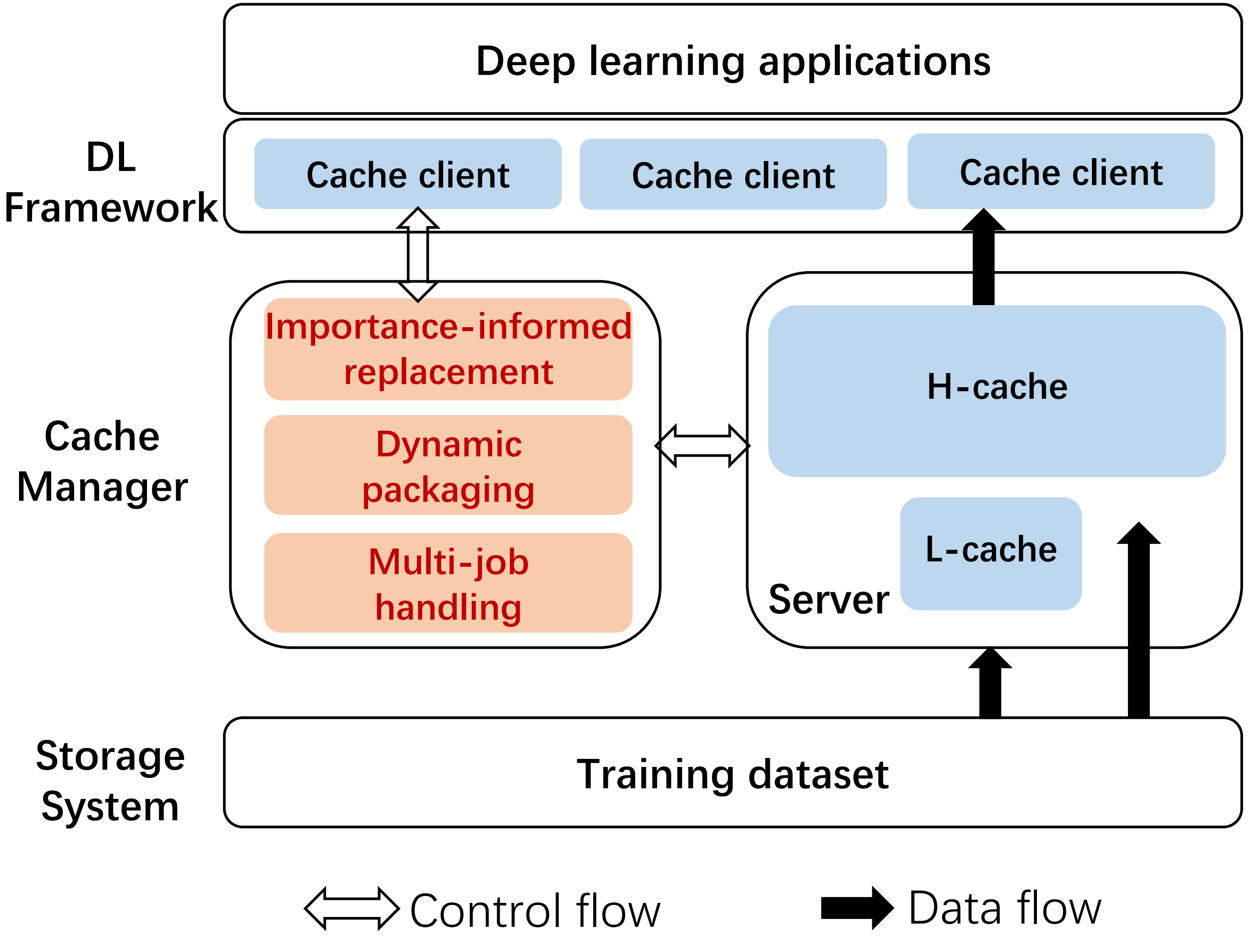
- Maintains each data item's importance value
- Requests data items based on Importance sampling algorithm

Cache server

- User-level cache
- H-cache: cache H-samples
- L-cache: cache L-samples

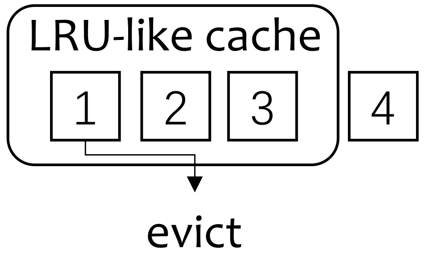
Cache Manager (Key ideas)

- Importance-informed cache replacement
- Dynamic packaging to serve L-sample requests
- Multi-job handling module



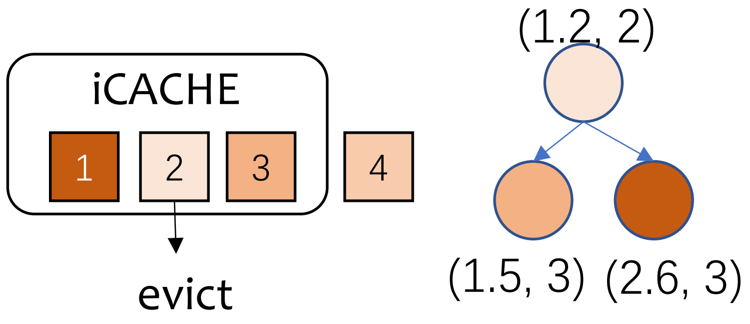
1. Importance-Informed Cache Algorithm

- Aims to serve H-sample requests and improve H-cache hit ratio.



(a) LRU-like algorithm

- **Use a small-top-heap for cache replacement.**
  - O(1) to find the data item with smallest importance value.
- **Tracks samples‘ importance value and refresh.**
- **Build shadow-heap to asynchronously update importance value.**
  - The additional space overhead is less than 0.5% of the cache size.



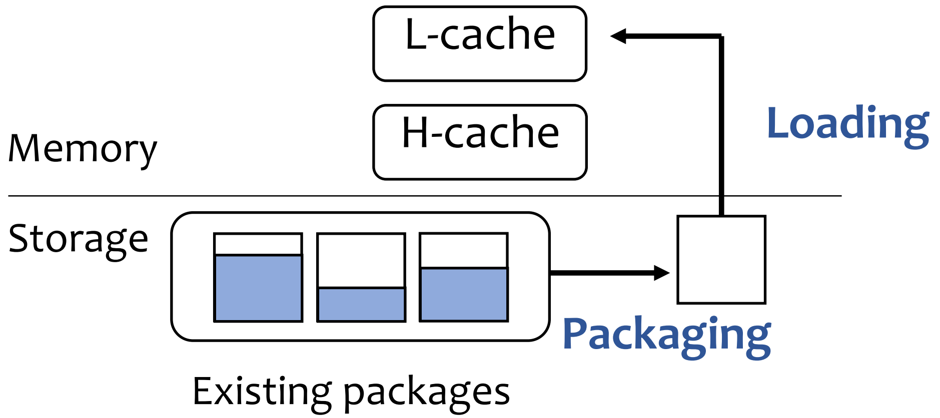
(b) iCACHE

2. Dynamic Packaging

- Aims to serve L-sample requests.

➢ Key idea:
  - **apply substitutability on L-samples** has minor impact on model accuracy while reducing data fetch time.

➢ **Two asynchronous concurrent threads**, packing and loading thread, to reduce the time cost of loading L-samples.



* The white area represents L-samples; the blue area denotes H-samples.

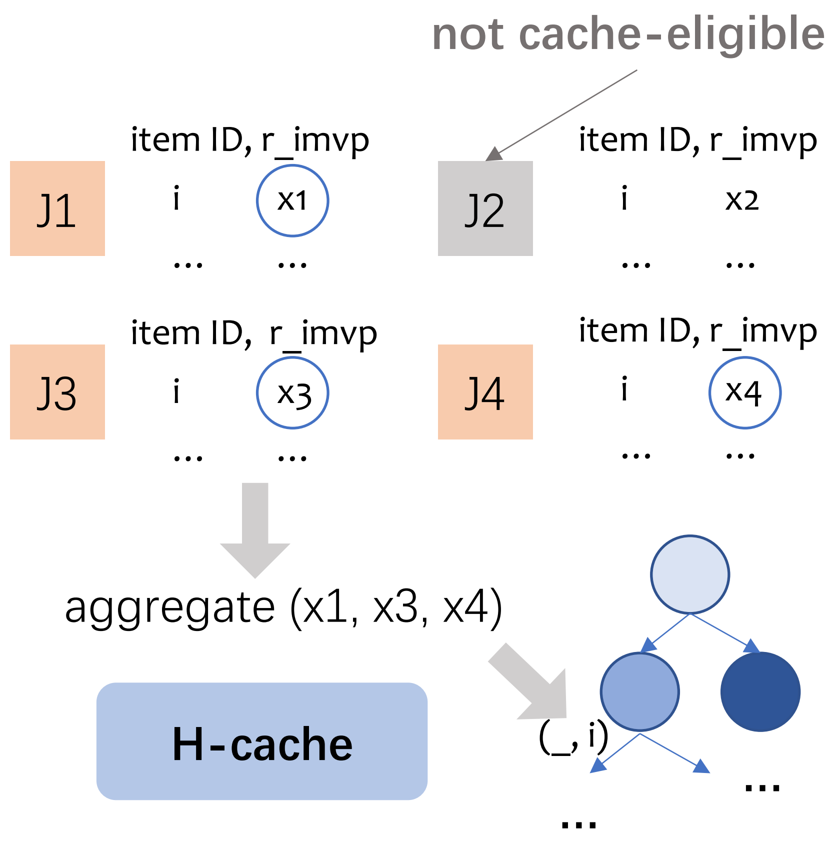
3. Multi-Job Handling

- One data item may receive different import-ance value

1. Evaluate the cost-effectiveness of caching for each job by profiling

2. Adjust importance value:

- use relative importance value
- calculate aggregated importance value



Implementation

- Cache client (2000 LOC)
  - New *Dataset* interface of PyTorch
- Cache server (3500 LOC)
  - Key-value structure in Golang
  - dynamic packaging & multi-job handling
- Easy to deploy iCACHE.
- We also extend iCACHE to the **distributed version.**

PyTorch (1.8.0)

Golang

Experimental Setup

➢ System configuration

CPU	2× AMD EPYC 7742 CPUs
GPU	8× NVIDIA A100
Dataset store	OrangeFS (Remote PFS), 10Gbps Ethernet.

➢ Workloads and datasets

Datasets	CIFAR10, ImageNet-1k
DNN Models	ShuffleNet, ResNet18, MobileNet, ResNet50, VGG11, MnasNet, SqueezeNet, and DenseNet121.

➢ Compared systems

Default	PyTorch + LRU user-level cache
Base	CIS + LRU user-level cache
Quiver [FAST'20]	Uses sample substitutability & Coordinated eviction
CoorDL [VLDB'21]	Does not evict already cached data
iLFU	IIS + LFU to compare different cache strategies

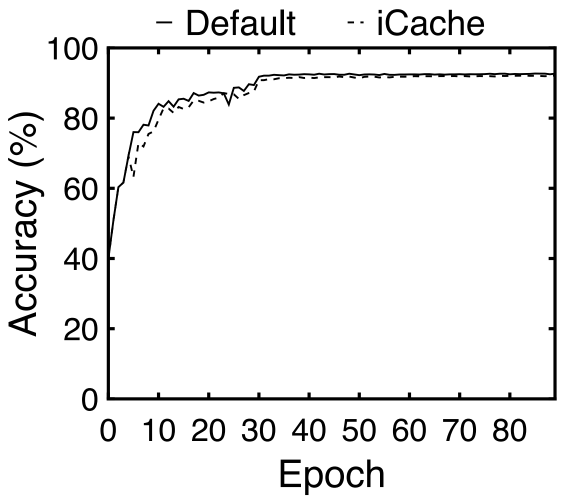
State-of-the-art

➢ Default cache size: 20% of total training dataset as Quiver does.

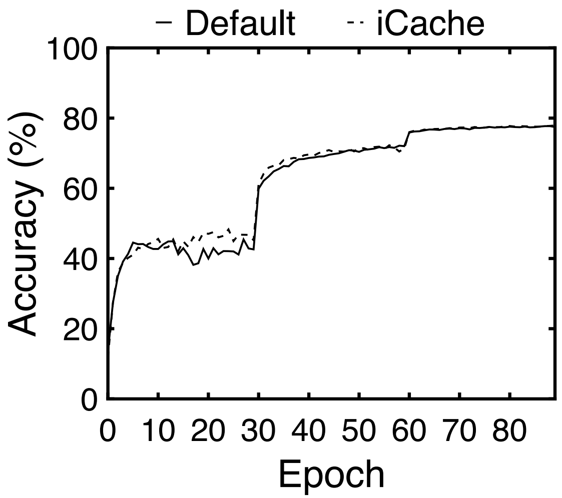
Accuracy

TABLE I
MODEL ACCURACY ON CIFAR10.

Models	Top-1 Acc.(%)		Top-5 Acc.(%)	
	Default	iCACHE	Default	iCACHE
ShuffleNet	87.76	86.96	99.59	99.57
ResNet18	92.70	92.14	99.81	99.80
MobileNet	92.37	92.01	99.87	99.77
ResNet50	89.91	89.36	99.68	99.69



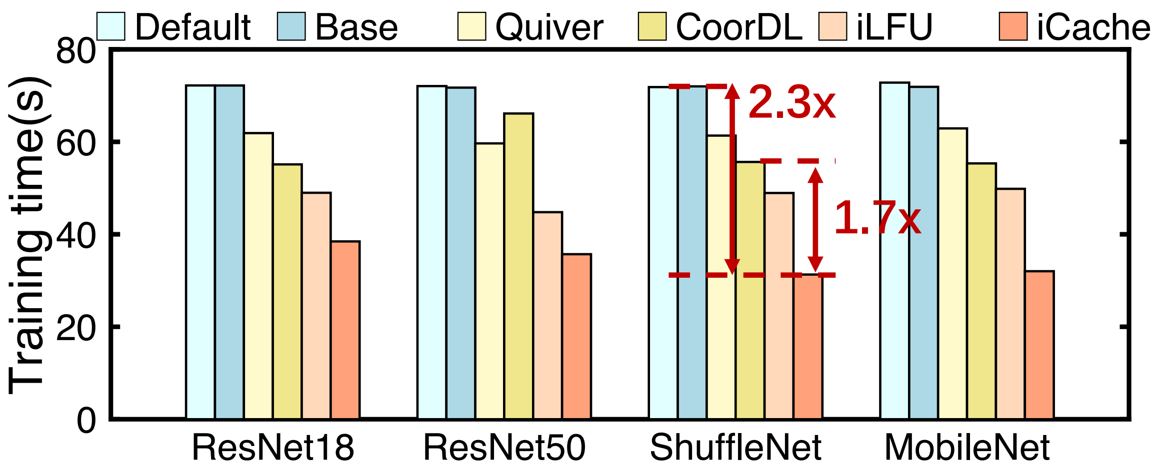
ResNet18 on CIFAR10

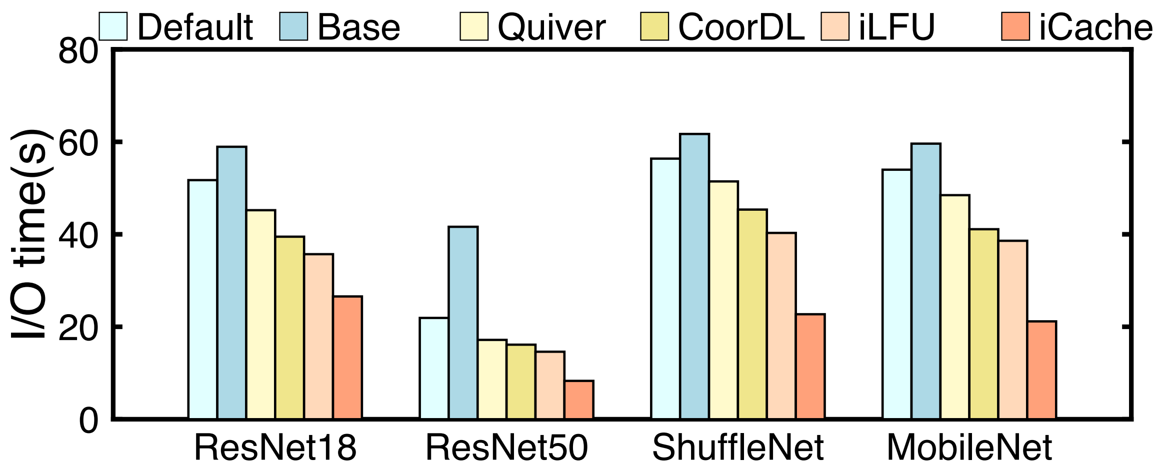


SqueezeNet on ImageNet

Comparable accuracy is achieved on different models and datasets

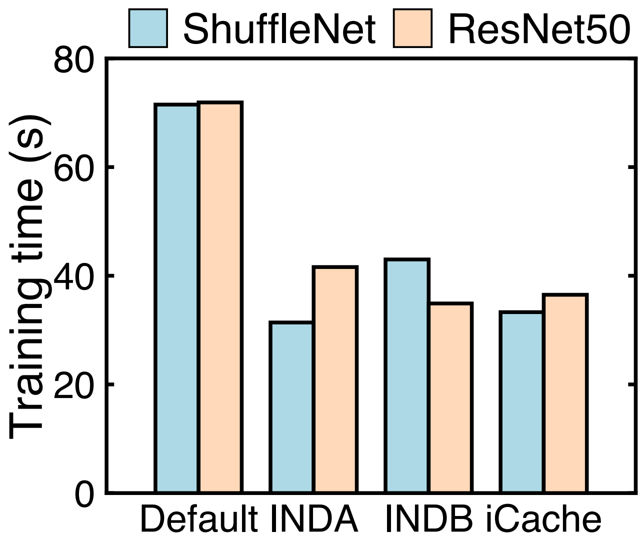
Overall Performance

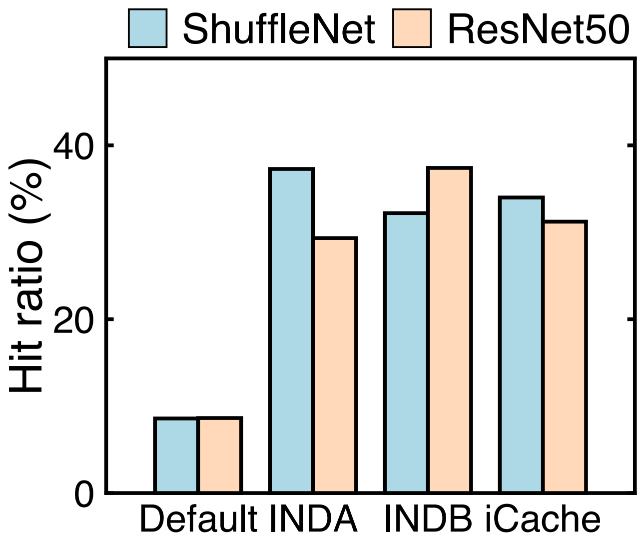




iCACHE speeds up the overall training time by 1.7x compared to SOTA, and 2.3x to Base. Compared to Default, iCACHE reduces the I/O time by 2.4x on average.

Multi-job Training Performance

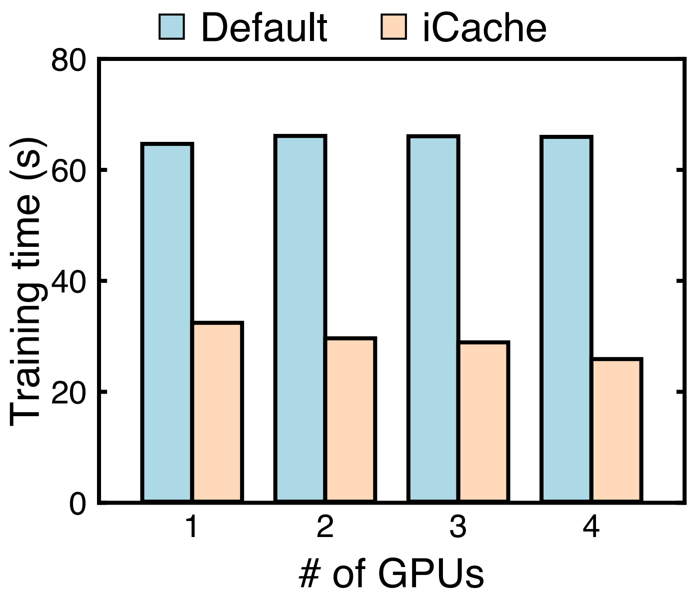




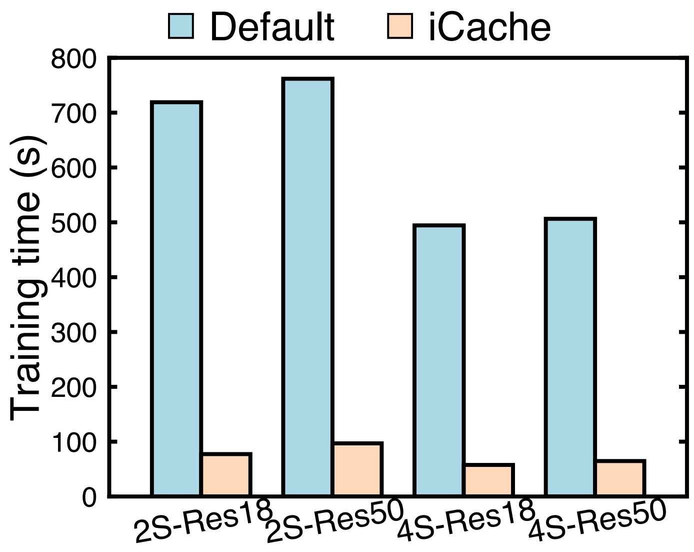
INDA: Manage cache simply based on importance value given by ShuffleNet.
INDB: Manage cache simply based on importance value given by ResNet50.

iCACHE speeds up the jobs completion time in multi-job scenario by up to 1.2x.

Multi-GPU and multi-node training



(a) Multi-GPU training



(b) Multi-node training

iCACHE always performs better than Default on Multi-GPU training.
iCACHE speeds up at least 8.6x and 7.6x under 2-server and 4-server configurations.

More evaluations: checkout our paper.

Summary & Conclusion

- **Problem**
  - I/O is becoming the bottleneck in DNN training
- **Key idea**
  - Introduce I/O-oriented importance sampling (IIS) and optimize cache management considering importance values.
- **Techniques in iCACHE**
  - Importance-Informed Cache Algorithm
  - Dynamic Packaging
  - Multi-Job Handling
- **Results**
  - iCACHE alleviates I/O bottleneck of DNN training in various training scenarios.
  - iCACHE outperforms state-of-the-arts while maintaining comparable accuracy.

Thanks & QA

iCACHE: An Importance-Sampling-Informed Cache for Accelerating I/O-Bound DNN Model Training

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Code: https://github.com/ISCS-ZJU/iCache.

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