FLEET: Flexible Efficient Ensemble Training for Heterogenous Deep Neural Networks

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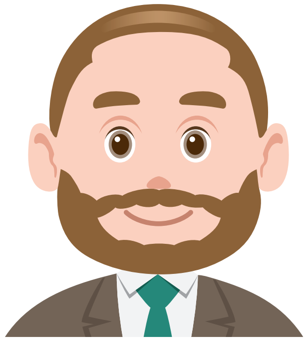
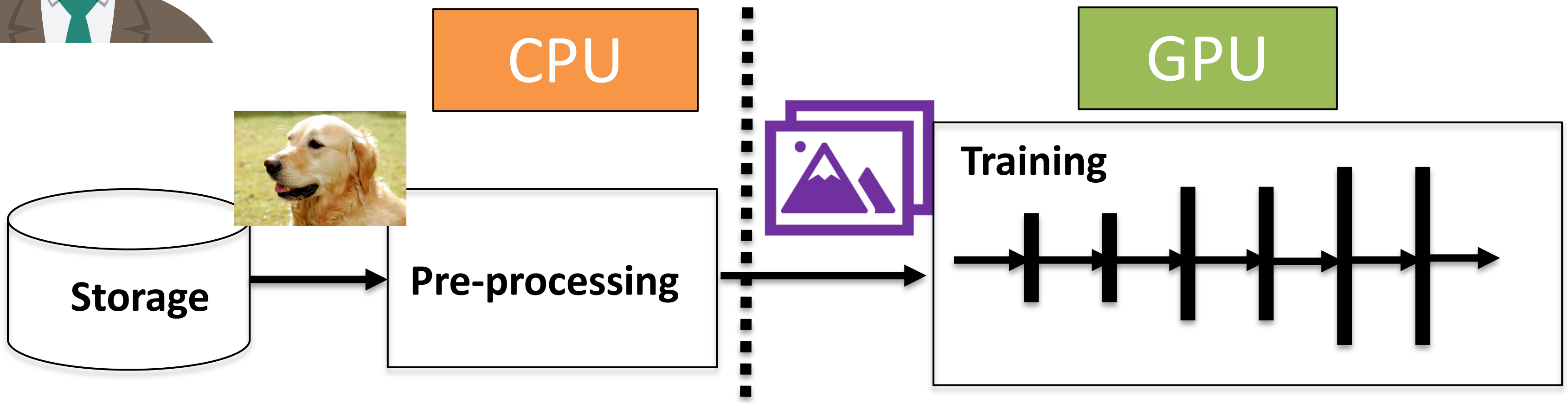


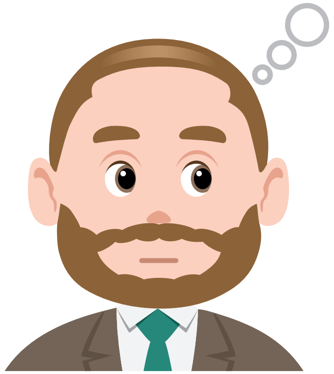
Build an image classifier? Deep Neural Network (DNN)



Decoding
Rotation
Cropping
…

Hyperparameters tuning:

- # layers
- # parameters in each layer
- Learning rate scheduling
- …



Ensemble Training

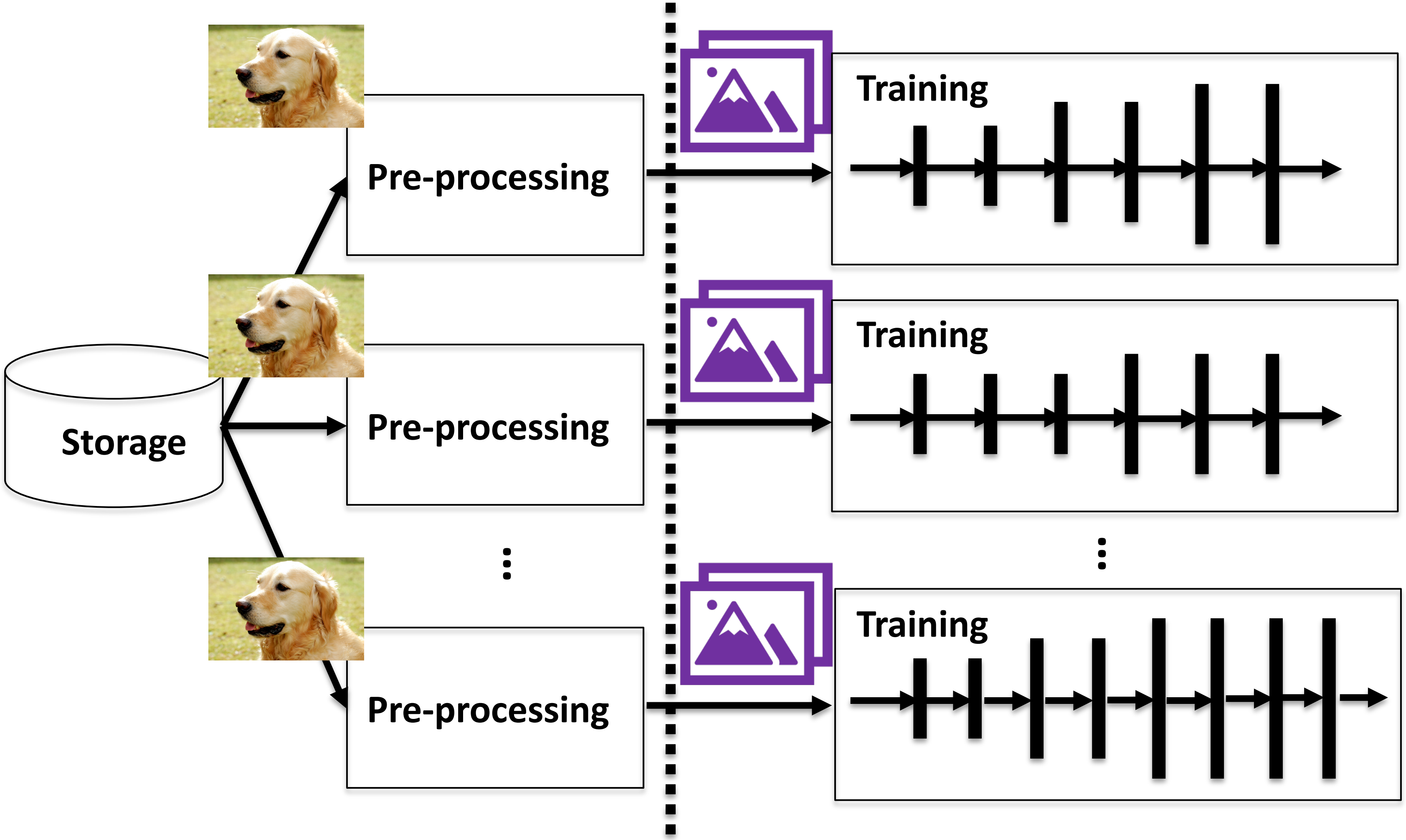
- concurrently train a set of DNNs on a cluster of nodes.

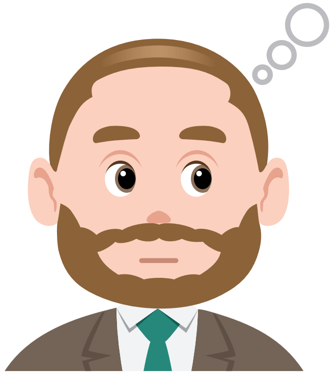
Train model 1

Train model 2

⋮

Train model N





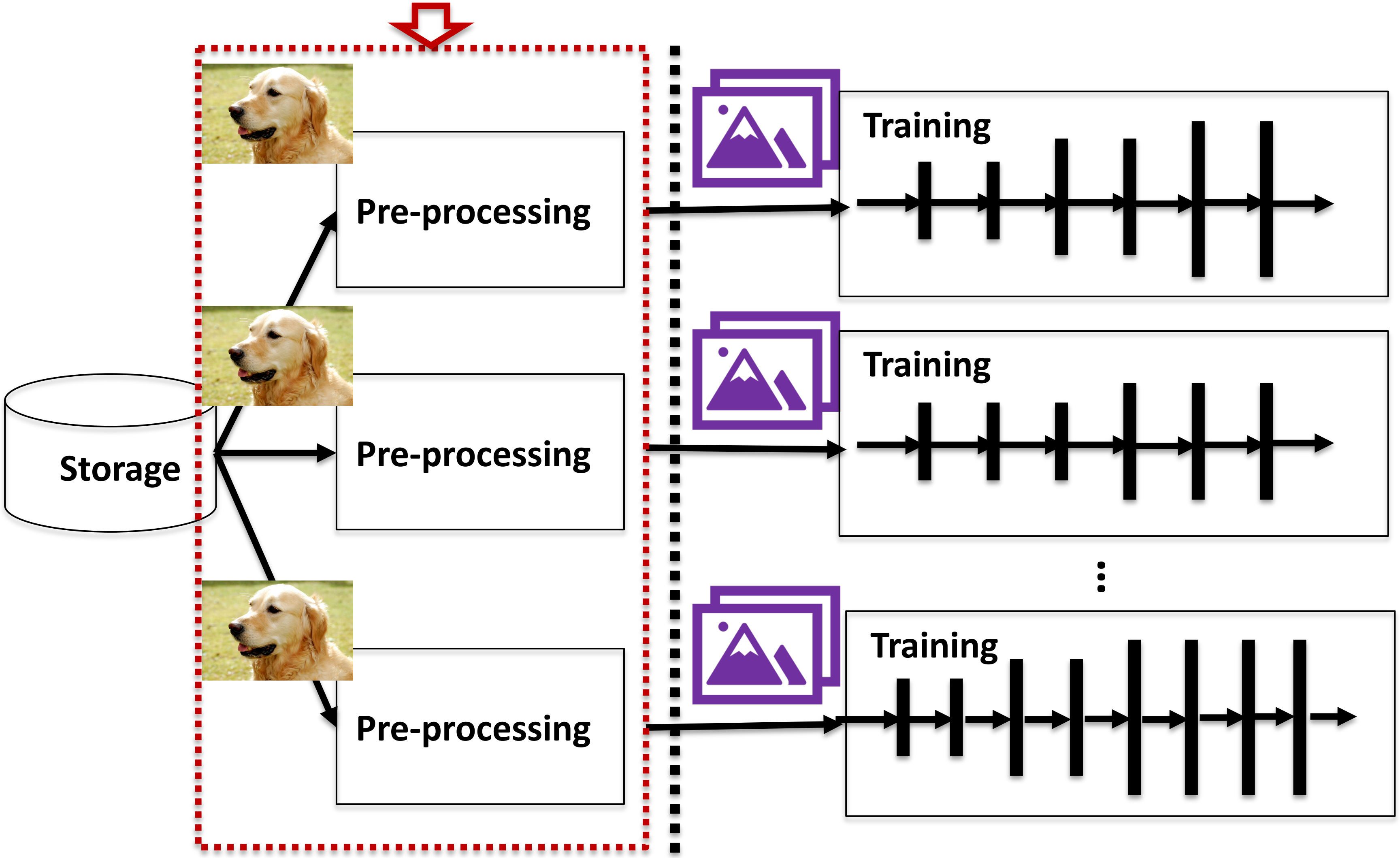
Preprocessing is redundant across the pipelines.

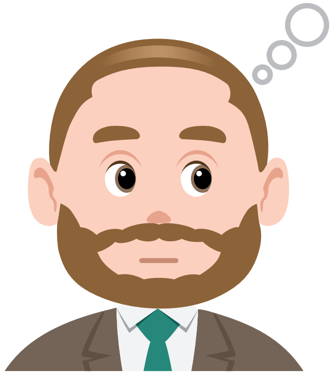
Train model 1

Train model 2

⋮

Train model N





Pittman et al., 2018

Eliminate pipeline redundancies in preprocessing through ***data sharing***

- Reduce CPU usage by 2-11X
- Achieve up to 10X speedups with 15% energy consumption

Pittman, Randall, et al. "Exploring flexible communications for streamlining DNN ensemble training pipelines." *SC18: International Conference for High Performance Computing, Networking, Storage and Analysis*. IEEE, 2018.

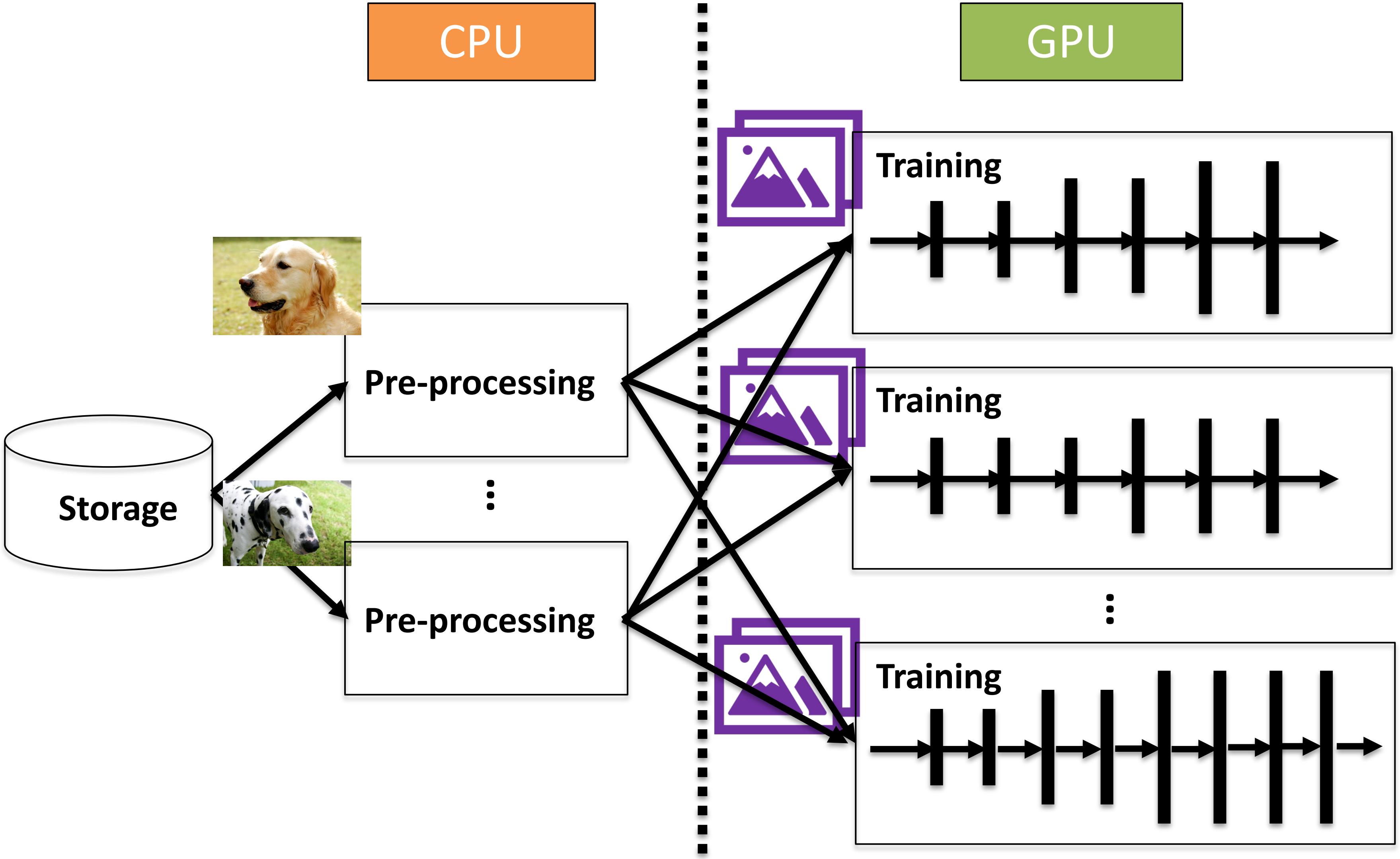
Ensemble training with ***data sharing***

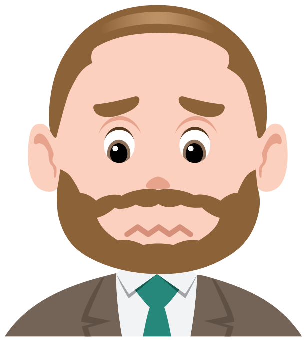
Train model 1

Train model 2

⋮

Train model N





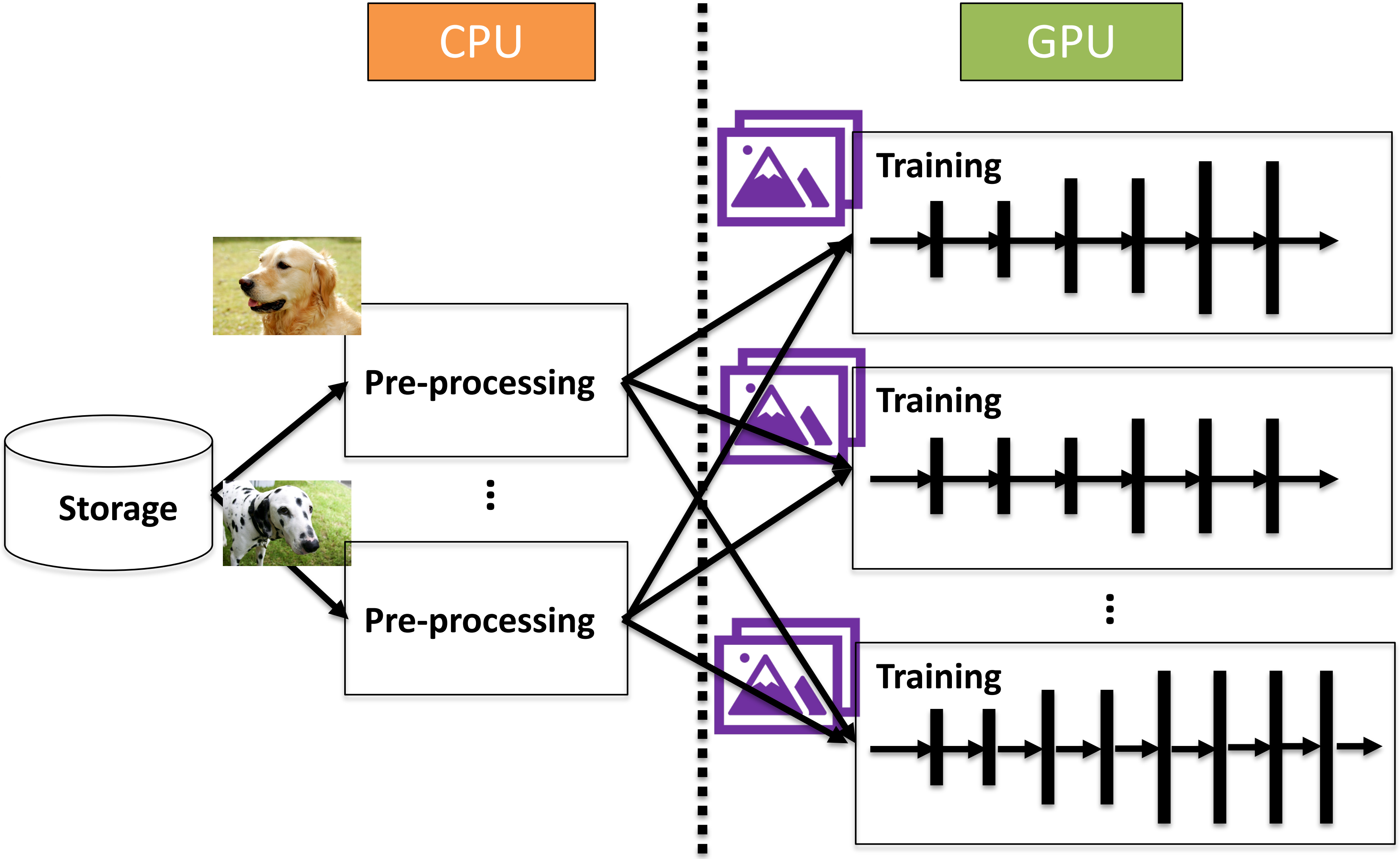
With data sharing, the training goes even slower!

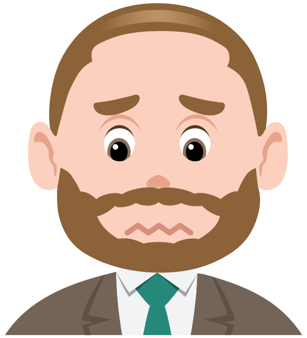
Train model 1

Train model 2

⋮

Train model N



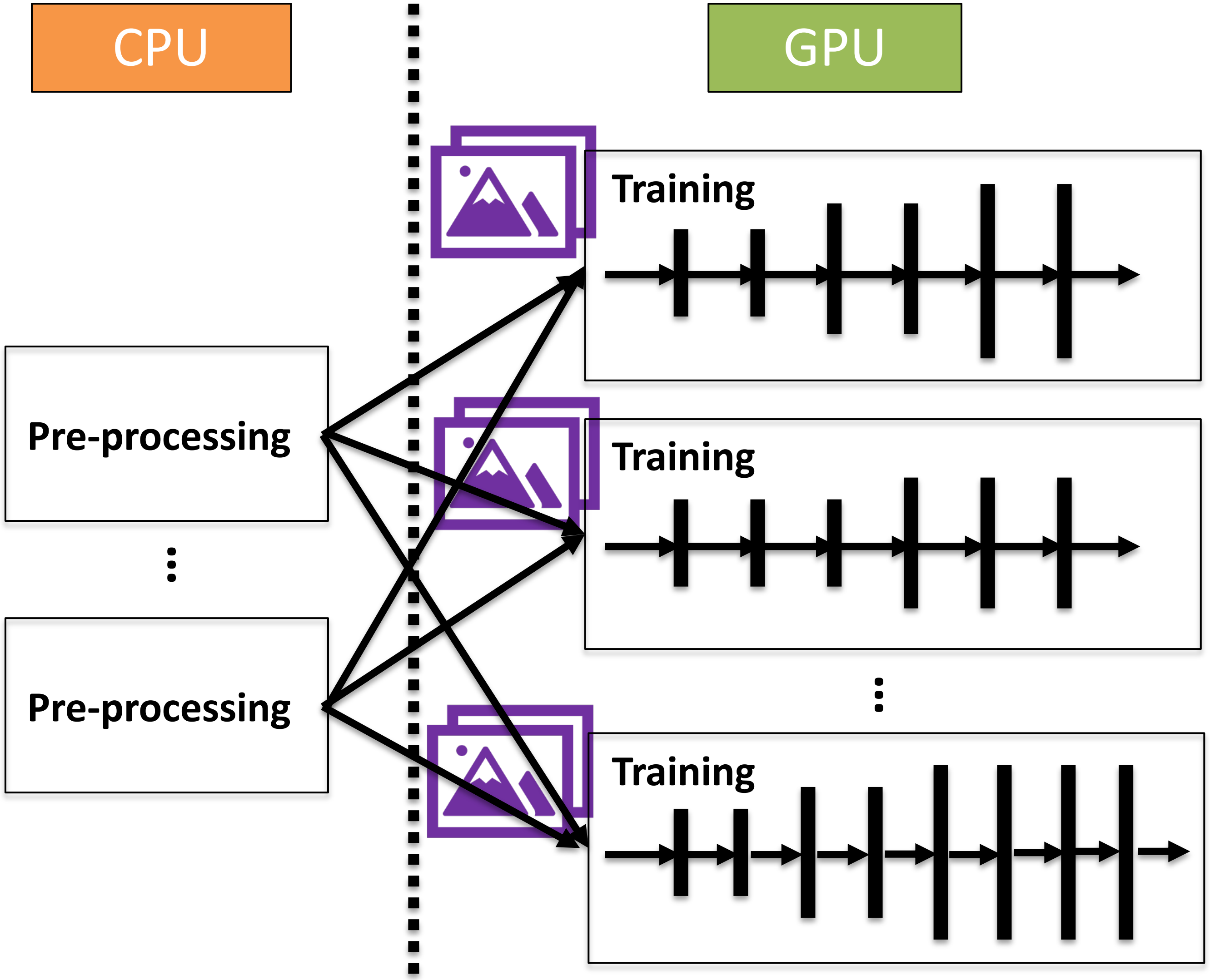


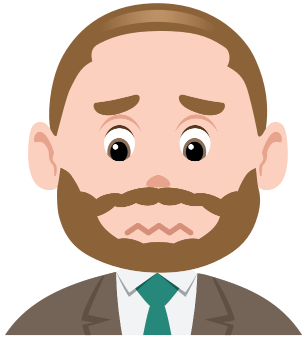
Heterogenous Ensemble

A set of DNNs with different architectures and configurations.

Varying training rate

Varying convergence speed

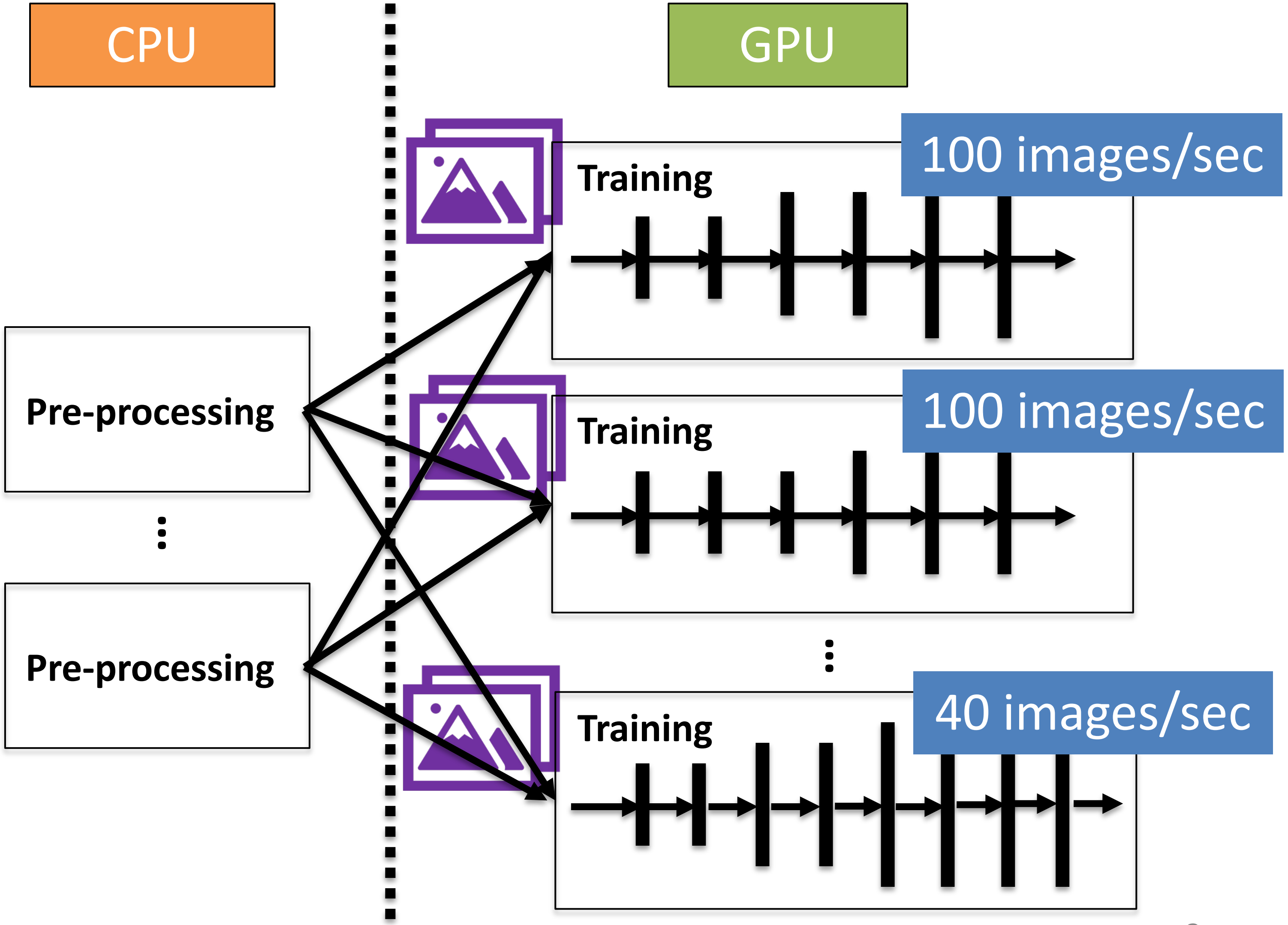


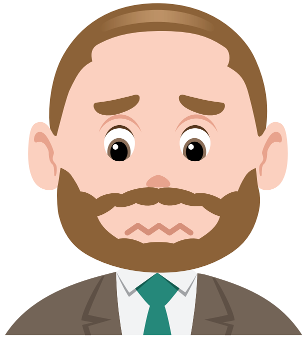


Heterogenous Ensemble

Varying training rate

Training rate:
compute throughput of processing units used for training the DNN.

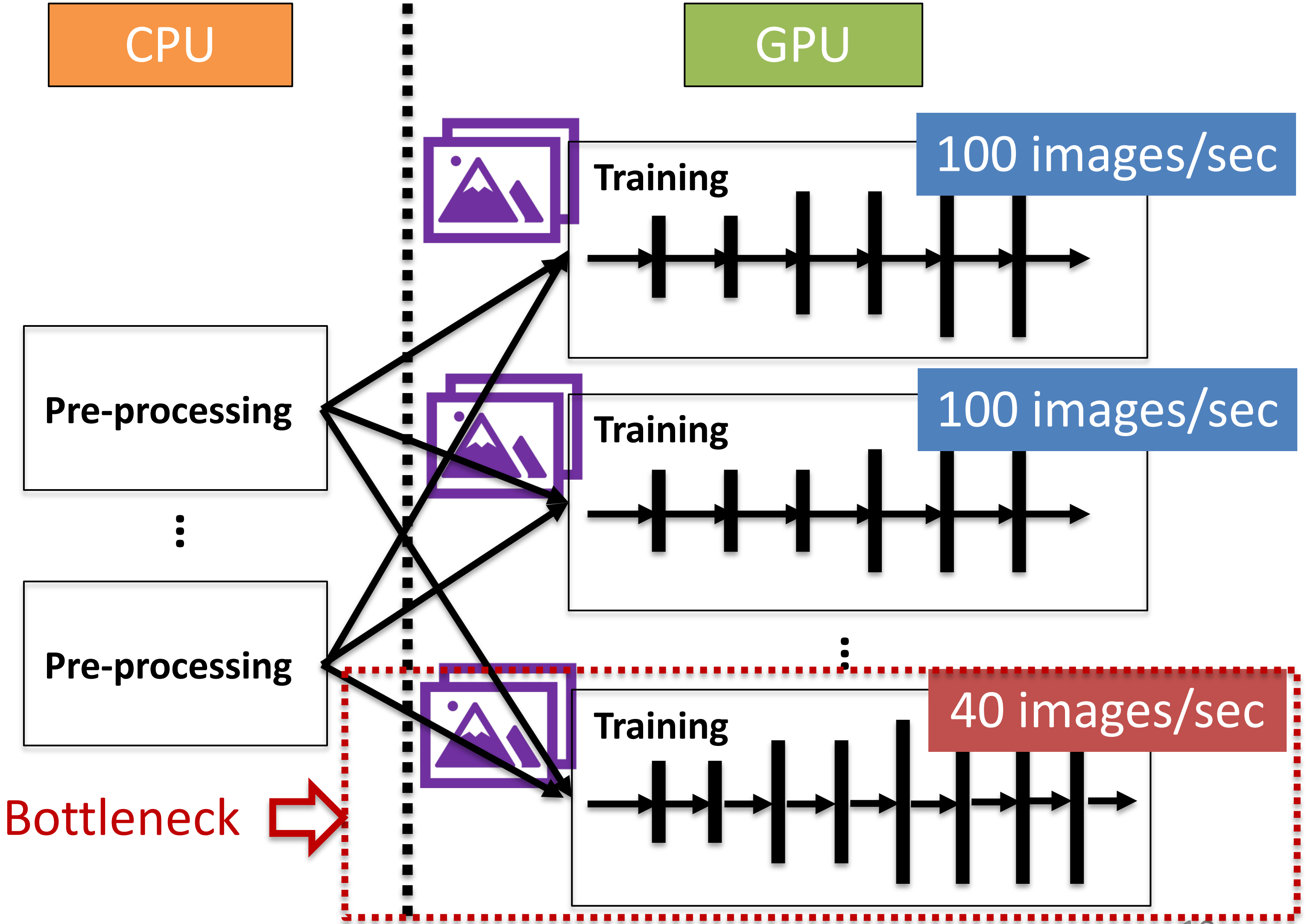


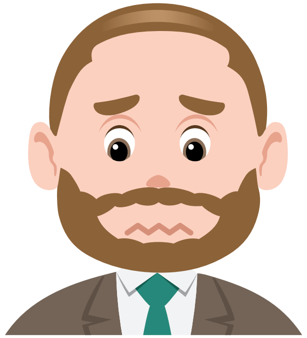


Heterogenous Ensemble

Varying training rate

If a DNN consumes data slower, other DNNs will have to wait for it before evicting current set of cached batches.



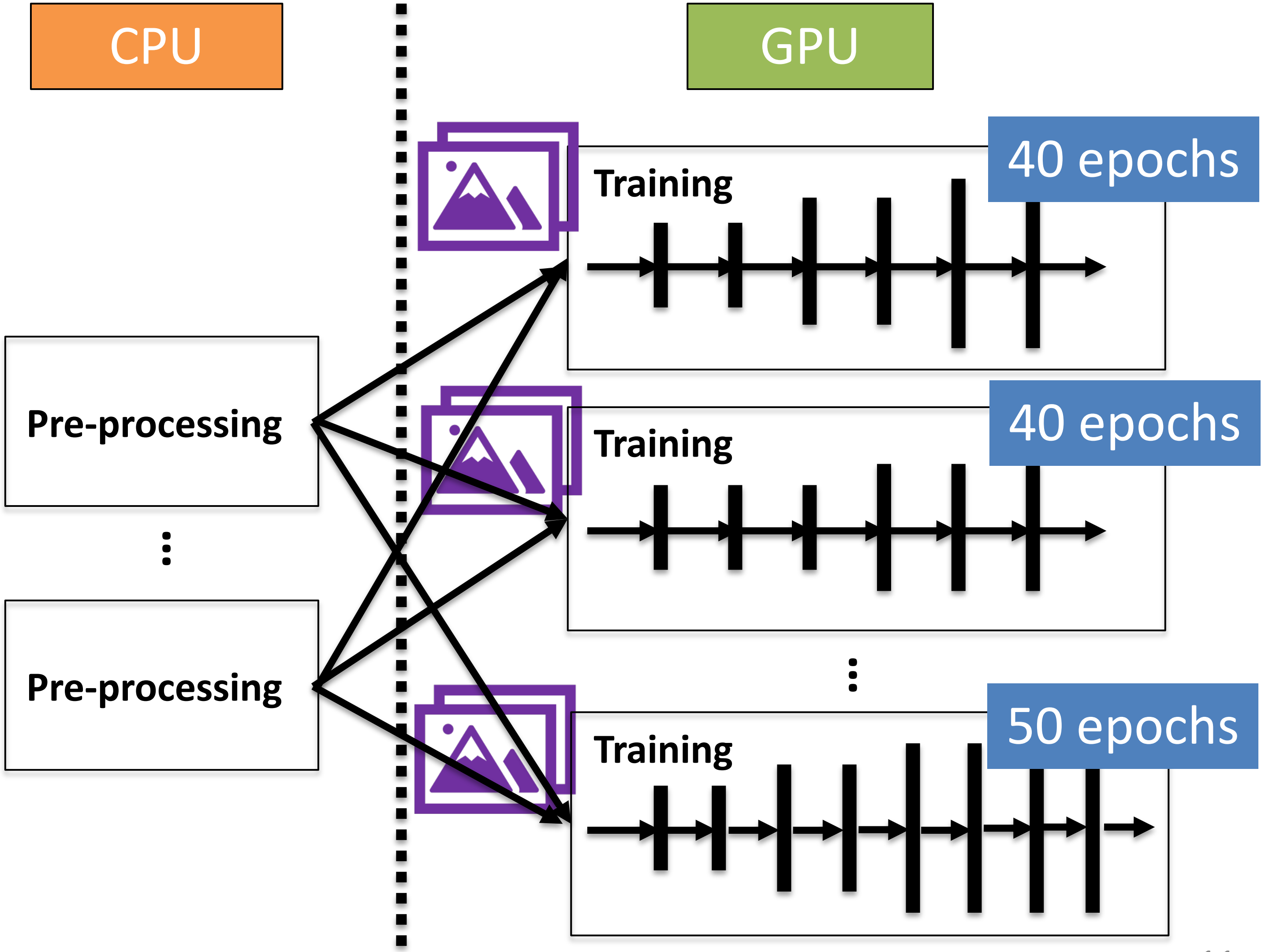


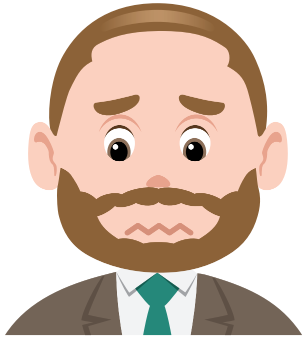
Heterogenous Ensemble

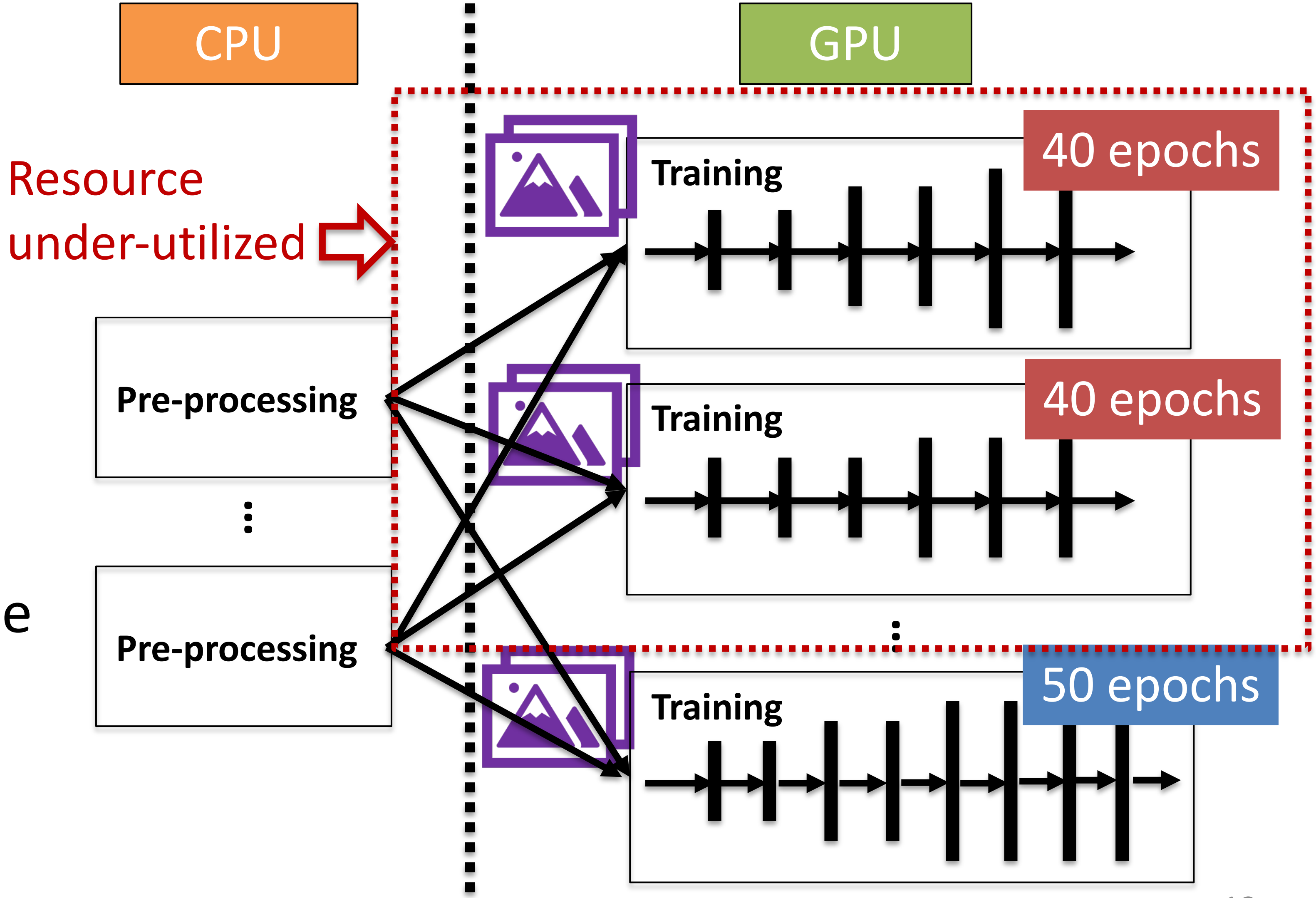
Varying training rate

Varying convergence speed

Due to differences in architectures and hyper-parameters, some DNNs converge slower than others.







Heterogenous Ensemble

Varying training rate

Varying convergence speed

A subset of DNNs have already converged while the shared preprocessing have to keep working for the remaining ones.

Our solution: FLEET

heterogenous ensemble

Varying training rate
Varying convergence speed

A *flexible* ensemble training framework for *efficiently* training a heterogenous set of DNNs.

1.12 – 1.92X speedup

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heterogenous ensemble

Varying training rate
Varying convergence speed

A *flexible* ensemble training framework for *efficiently* training a heterogenous set of DNNs.

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Contributions:

1. Optimal resource allocation

Our solution: FLEET

A *flexible* ensemble training framework for *efficiently* training a heterogenous set of DNNs.

heterogenous ensemble

Varying training rate ← Data-parallel distributed training

Varying convergence speed ← Checkpointing

Contributions:

1. Optimal resource allocation
2. Greedy allocation algorithm

Our solution: FLEET

A *flexible* ensemble training framework for *efficiently* training a heterogenous set of DNNs.

heterogenous ensemble

Varying training rate ← Data-parallel distributed training

Varying convergence speed ← Checkpointing

Contributions:

1. Optimal resource allocation
2. Greedy allocation algorithm
3. A set of techniques to solve challenges in implementing FLEET

Focus of This Talk

A *flexible* ensemble training framework for *efficiently* training a heterogenous set of DNNs.

heterogenous ensemble

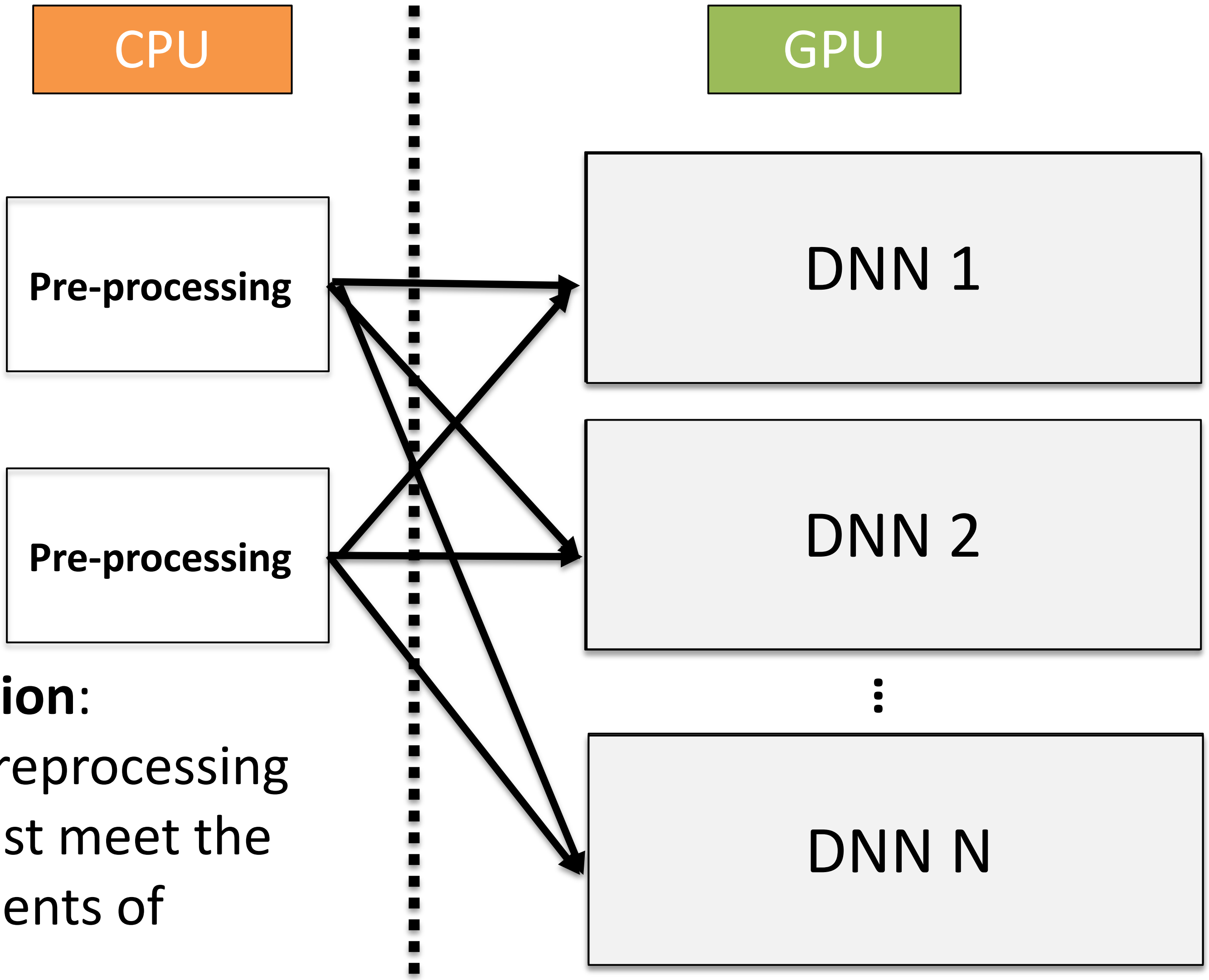
Varying training rate ← Data-parallel distributed training

Varying convergence speed ← Checkpointing

Contributions:

1. **Optimal resource allocation**
2. **Greedy allocation algorithm**
3. A set of techniques to solve challenges in implementing FLEET

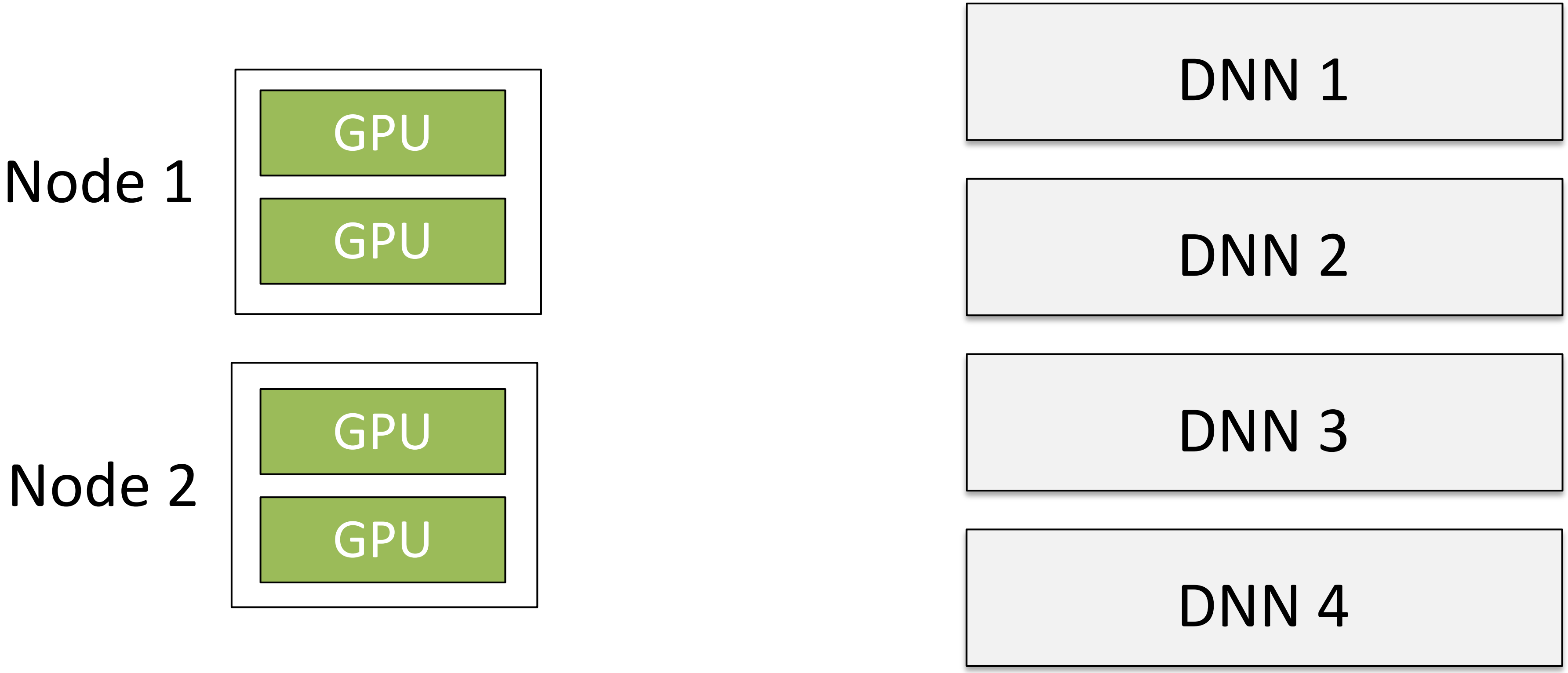
Resource Allocation Problem



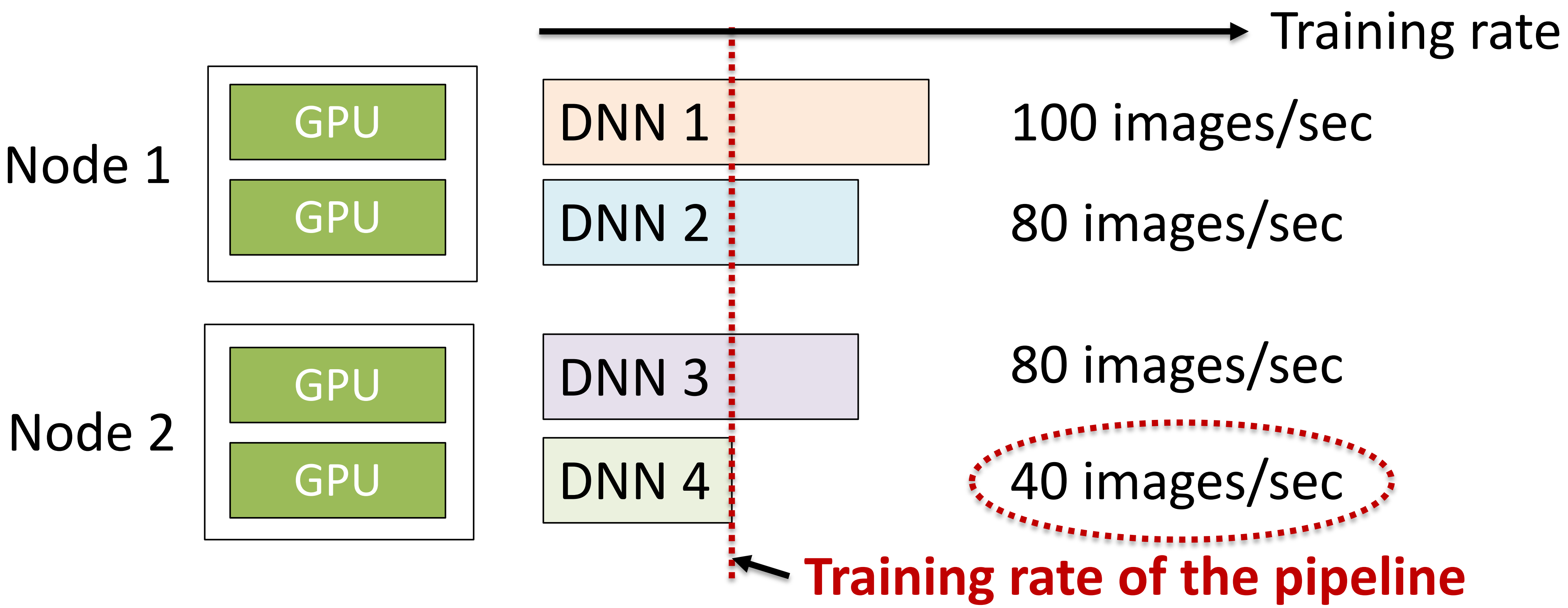
What is an **optimal GPU allocation**?

Optimal CPU allocation:
Set #processes for preprocessing to be the one that just meet the computing requirements of training DNNs

GPU Allocation

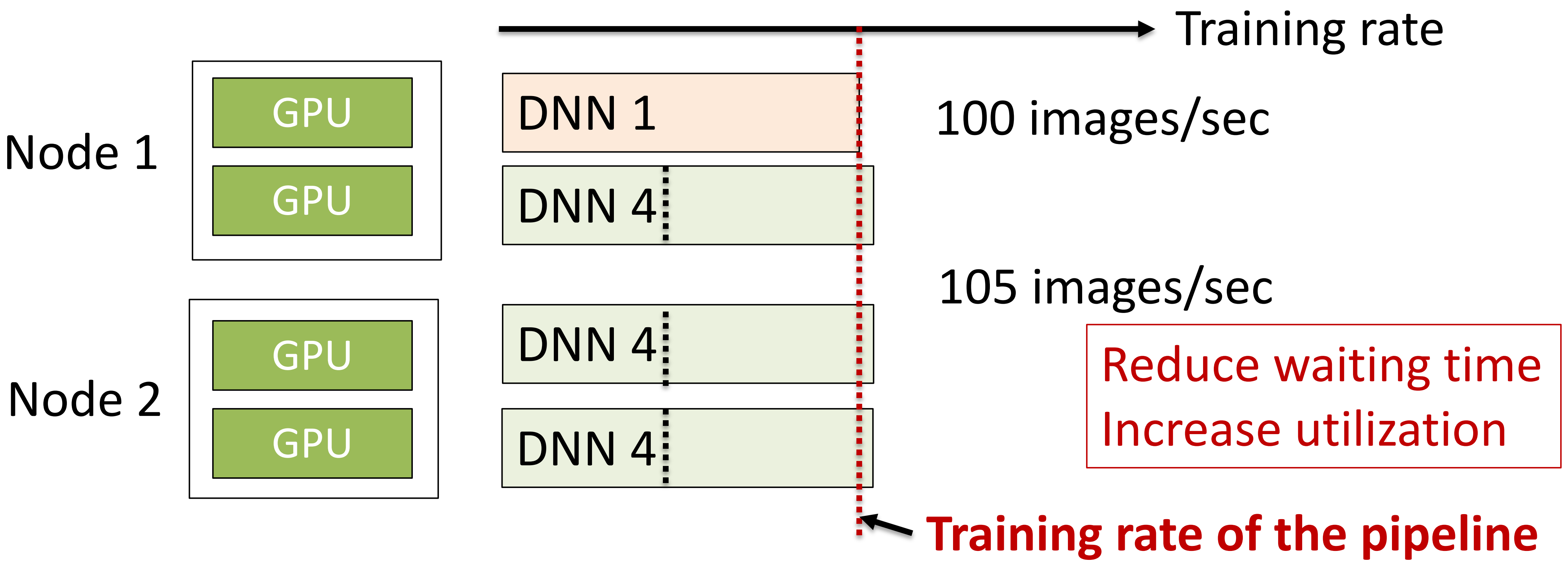


GPU Allocation: 1 GPU to 1 DNN



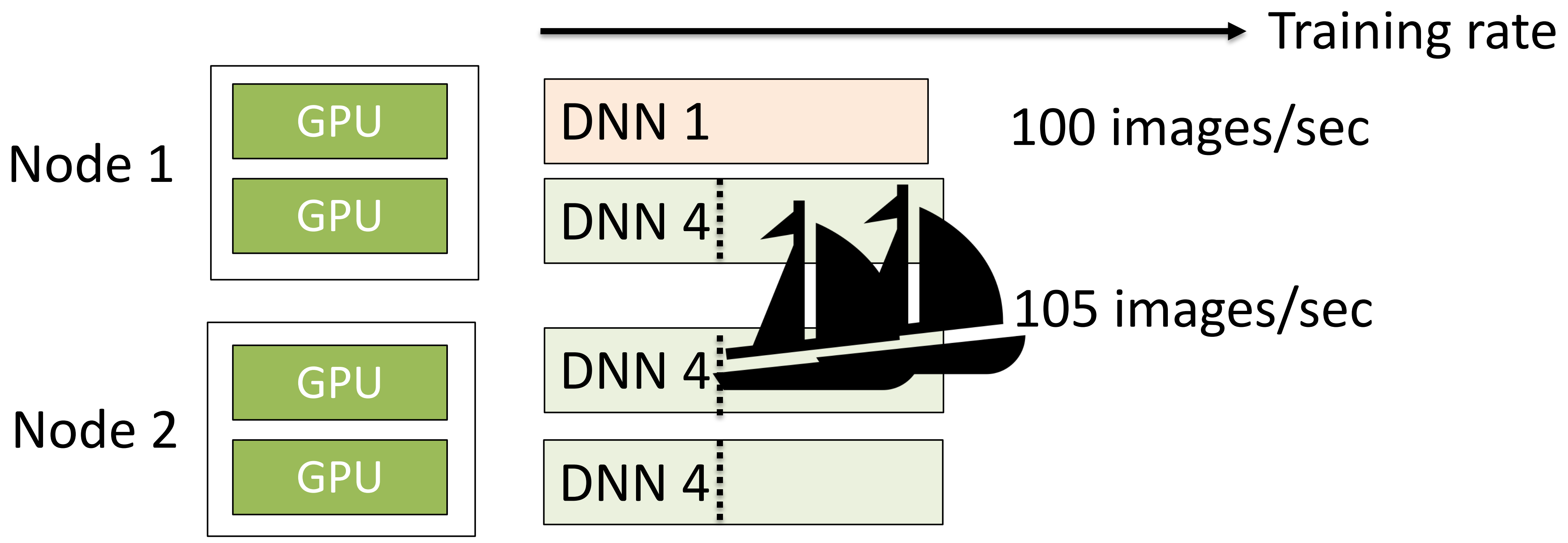
With data sharing, the slowest DNN determines the training rate of the ensemble training pipeline.

GPU Allocation: Different GPUs to Different DNNs



Another way to allocate GPUs: only DNN 1 and DNN 4 are trained together with data sharing.

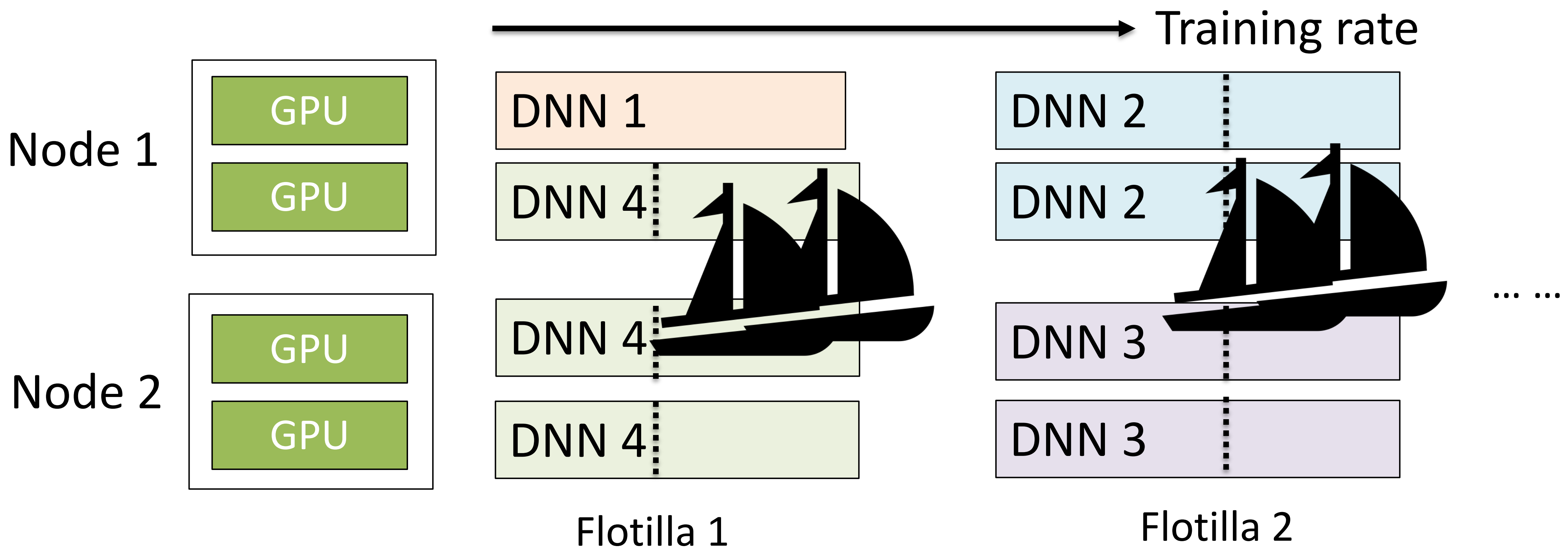
GPU Allocation: Different GPUs to Different DNNs



Flotilla

A set of DNNs to be trained together with data sharing (e.g., DNN1 and DNN4).

GPU Allocation: Different GPUs to Different DNNs



We need to create **a list of flotillas** to train all DNNs to converge.

Optimal Resource Allocation

Given a set of DNN to train and a cluster of nodes, find:
(1) the list of flotillas and
(2) GPU assignments within each flotilla
such that the end-to-end ensemble training time is minimized.

NP-hard

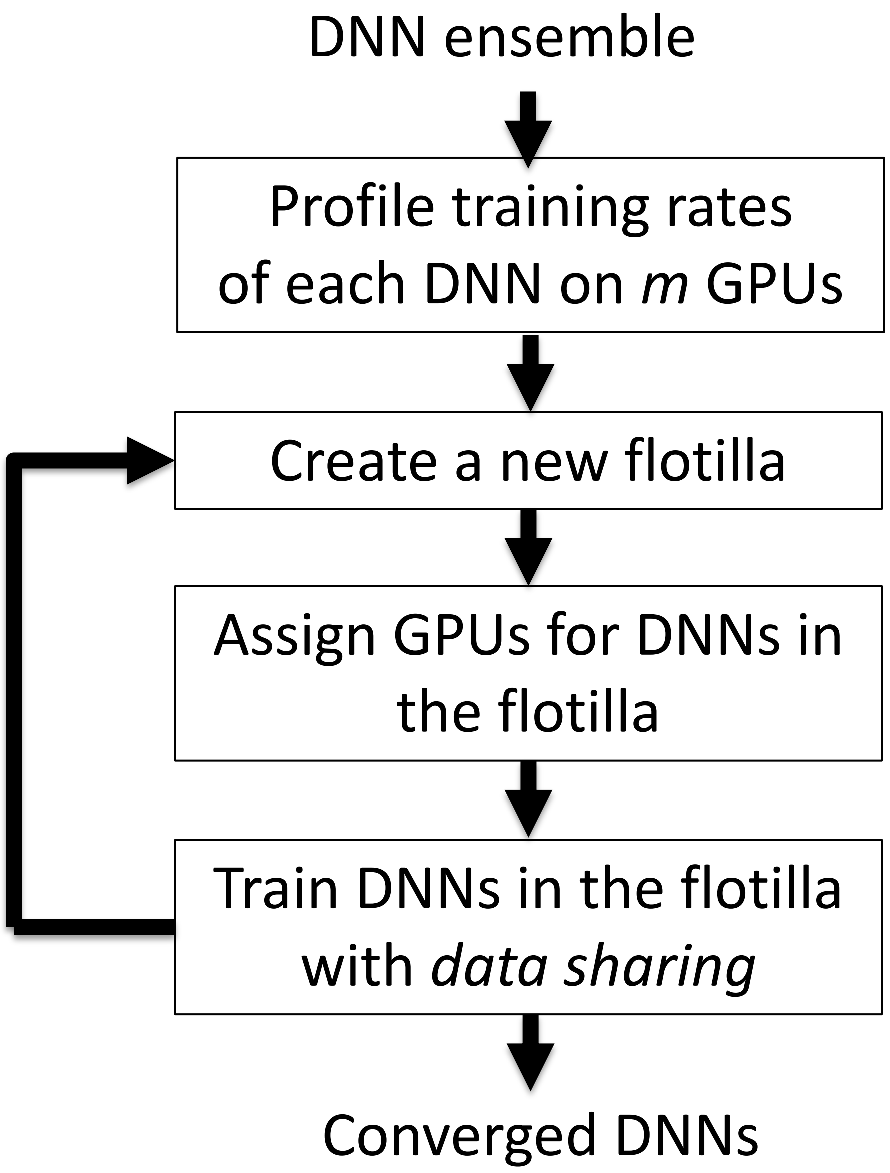
Greedy Allocation Algorithm

Dynamically determine **the list of flotillas**:
(1) whether a DNN is converged or not,
(2) the training rate of each DNN.

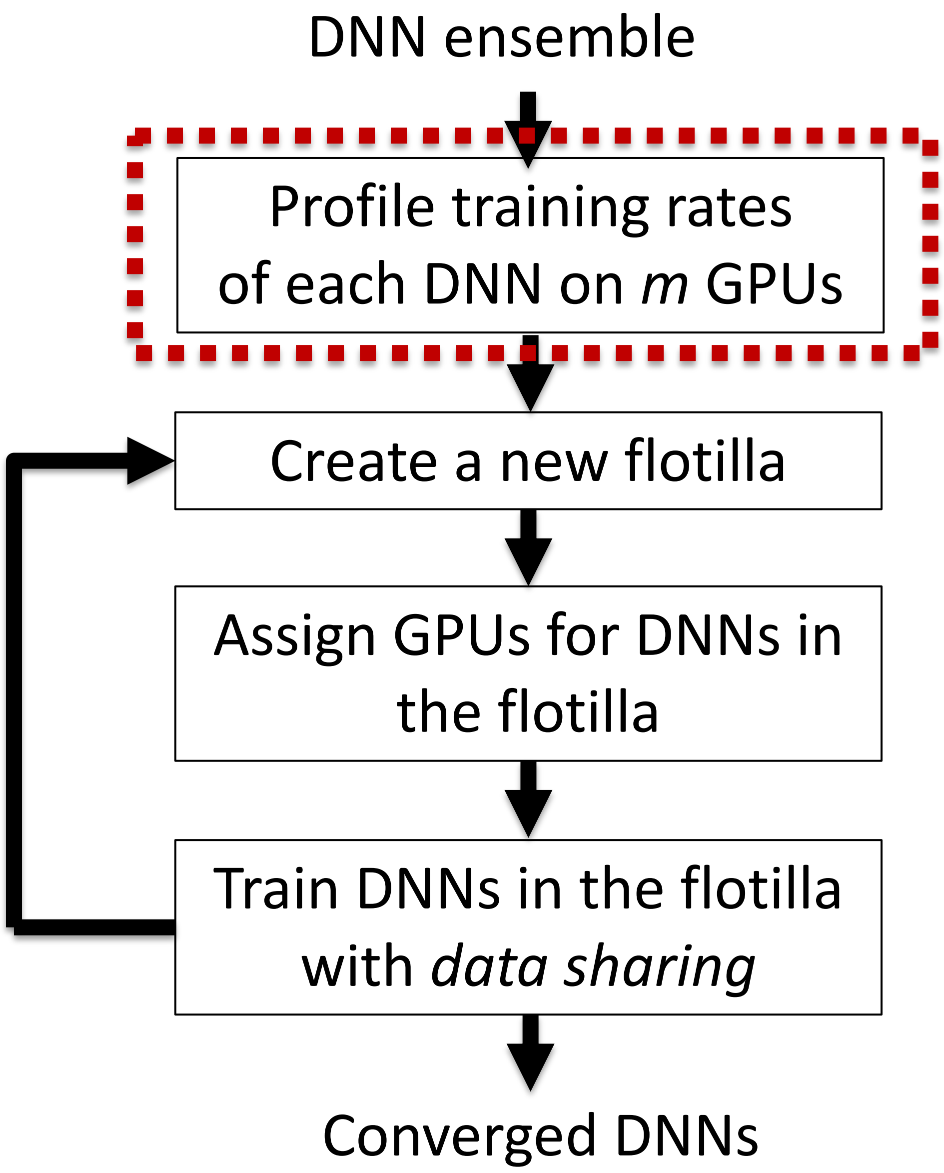
↓

Once a flotilla is created,
derive an optimal GPU assignment

Greedy Allocation Algorithm



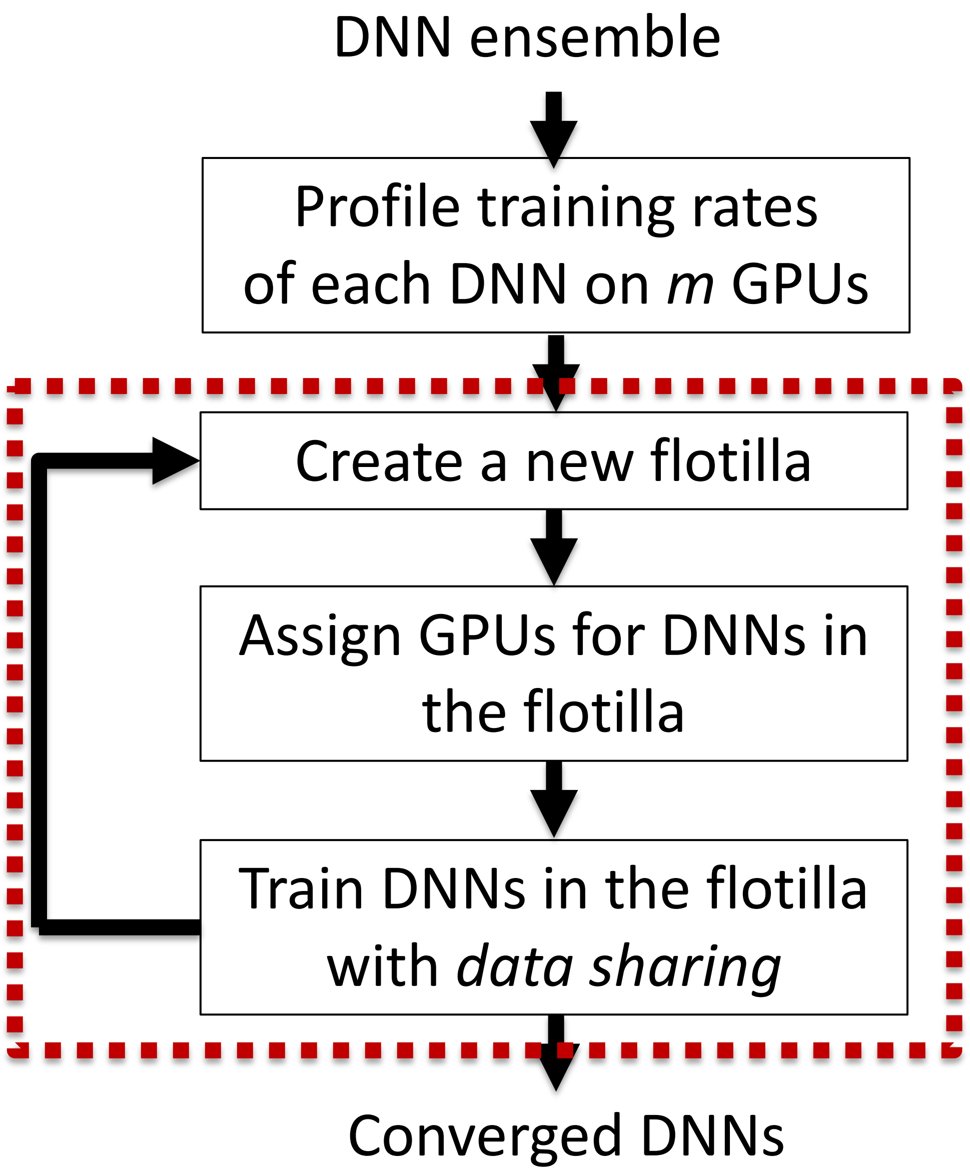
Greedy Allocation Algorithm: profiling



Training rates (images/sec) of DNNs on GPUs.

# GPU	1	2	3	4
DNN 1	100	190	270	350
DNN 2	80	150	220	280
DNN 3	80	150	200	240
DNN 4	40	75	105	120

Greedy Allocation Algorithm

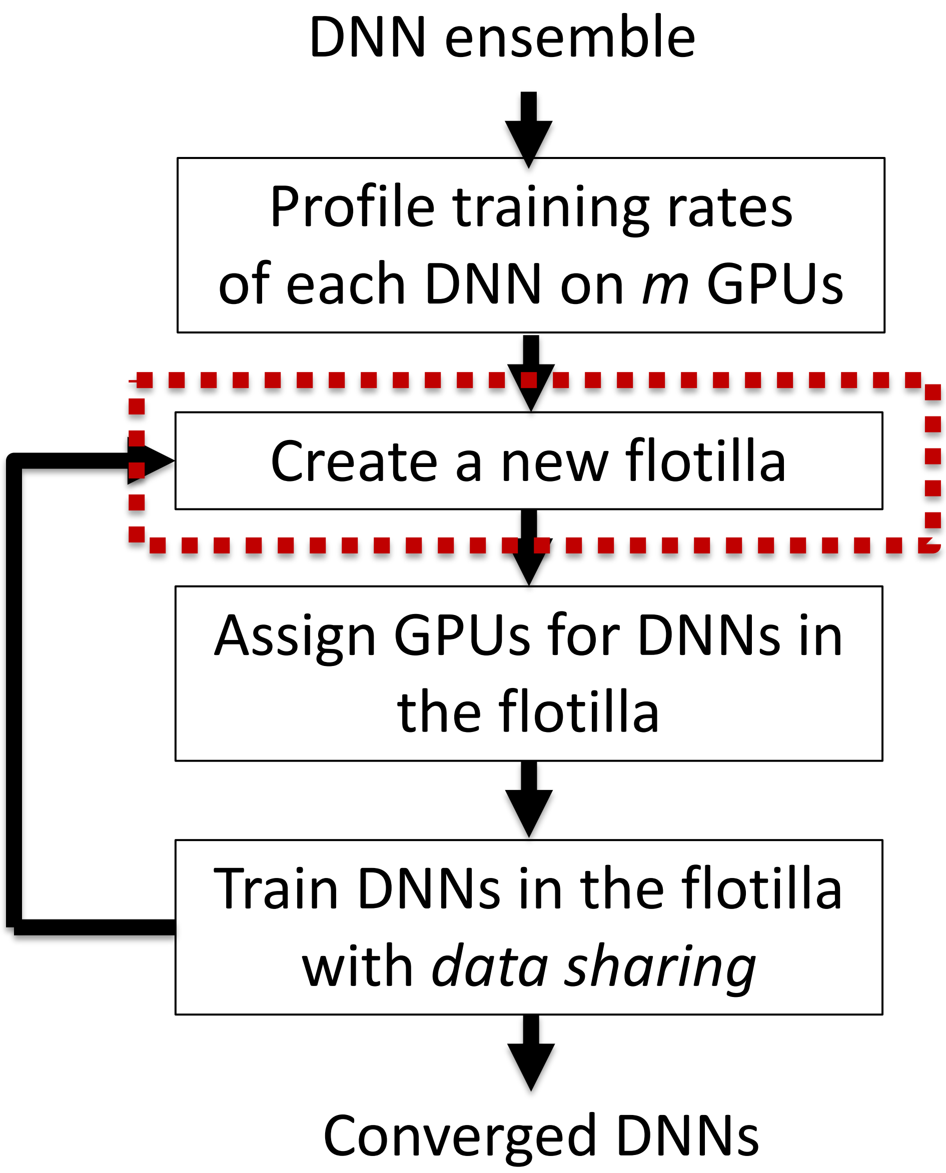


Step 1: Flotilla Creation

Step 2: GPU Assignment

Step 3: Model training

Step 1: Flotilla Creation



#1: DNNs in the same flotilla should be able to reach a similar training rate if a proper number of GPUs is assigned to each DNN.

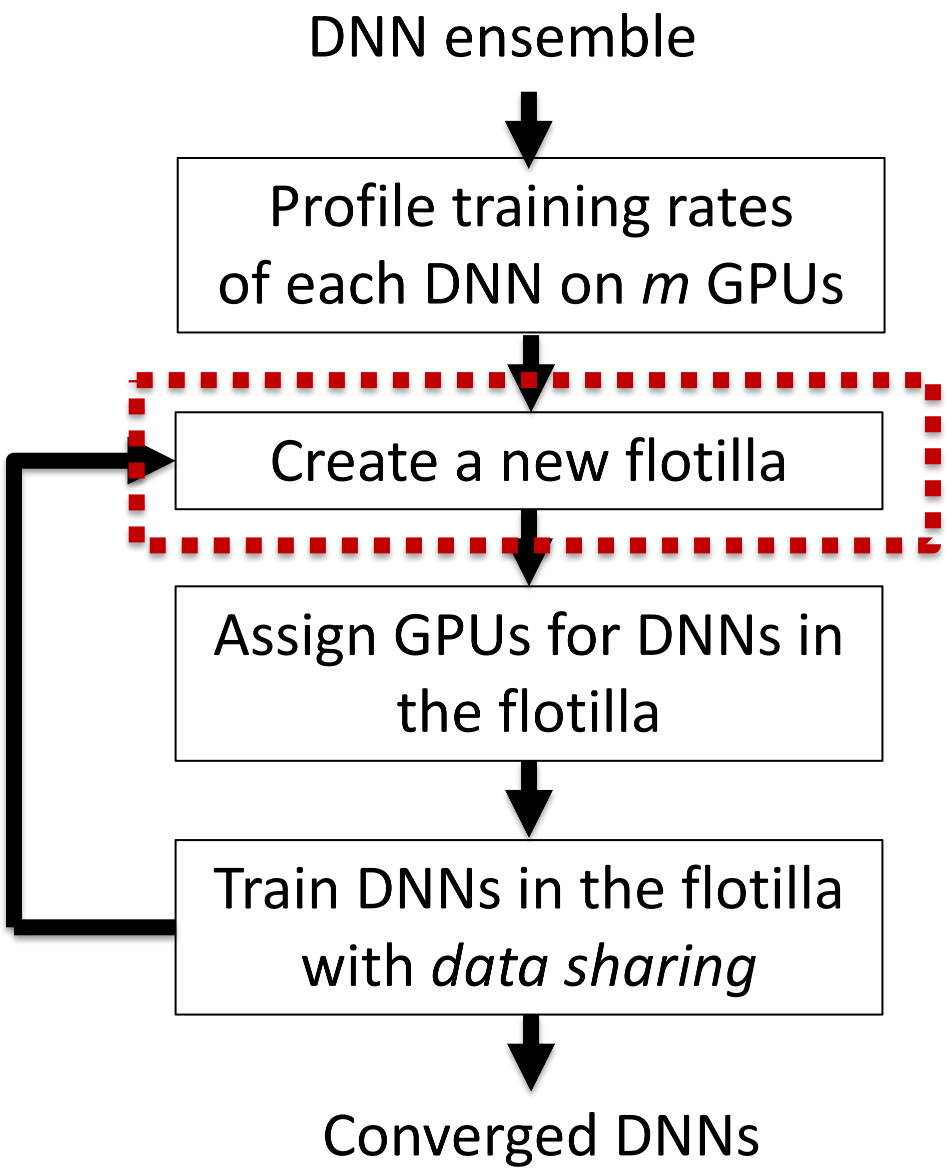
Reduce GPU waiting time

#2: Pack into one flotilla as many DNNs as possible.

Avoid inefficiency due to sublinear scaling

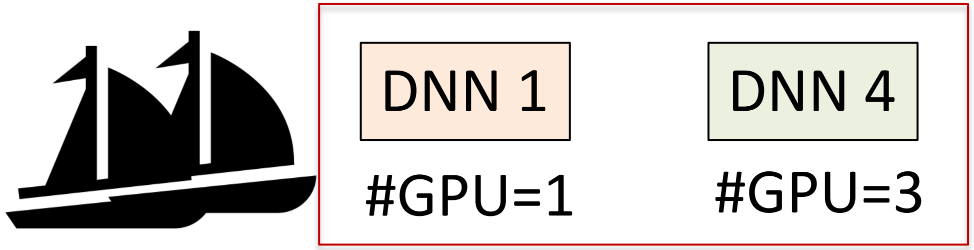
Allow more DNNs to share preprocessing

Step 1: Flotilla Creation

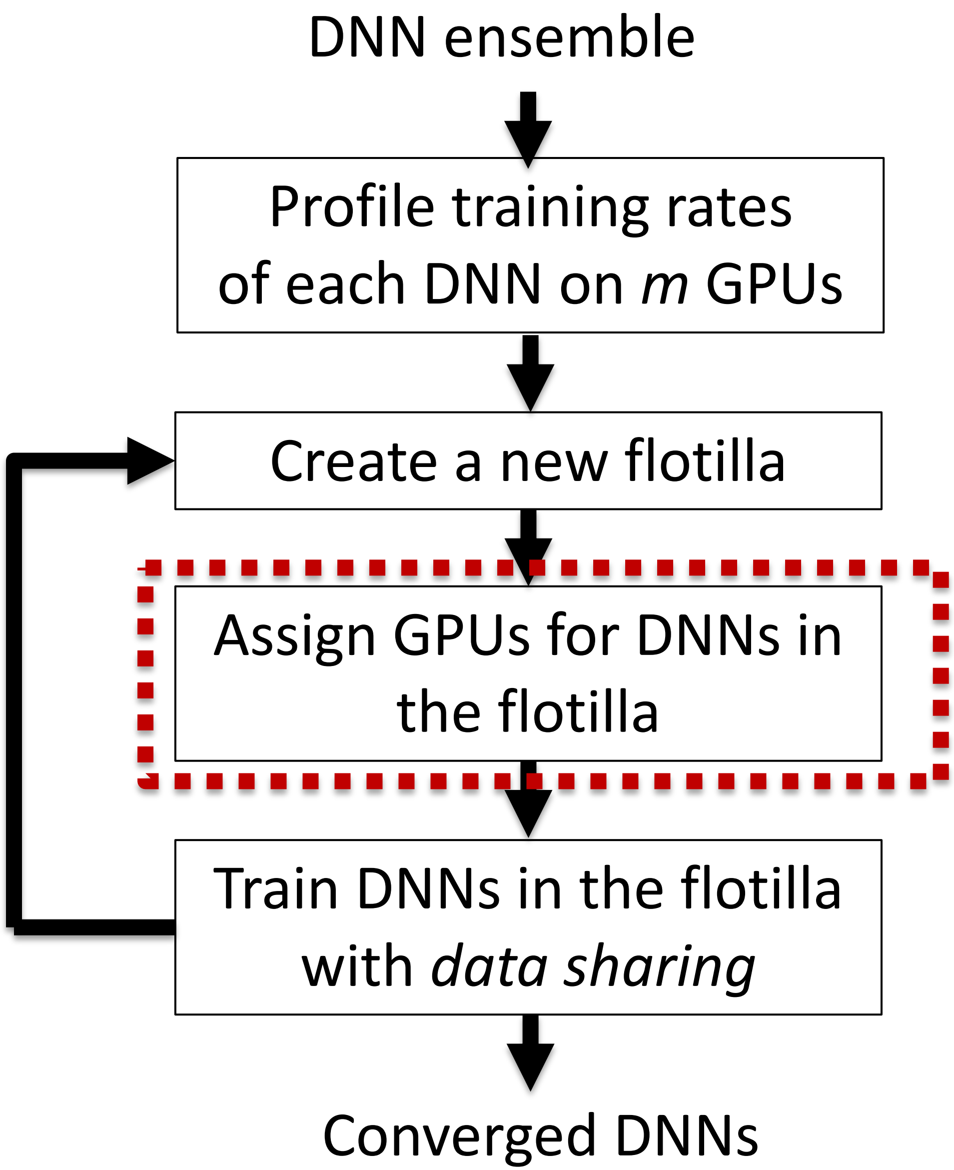


 # GPUs available: 4-1 → 3 – 3 → 0

# GPU	1	2	3	4
DNN 1	100	190	270	350
DNN 2	80	150	220	280
DNN 3	80	150	200	240
DNN 4	40	75	105	120



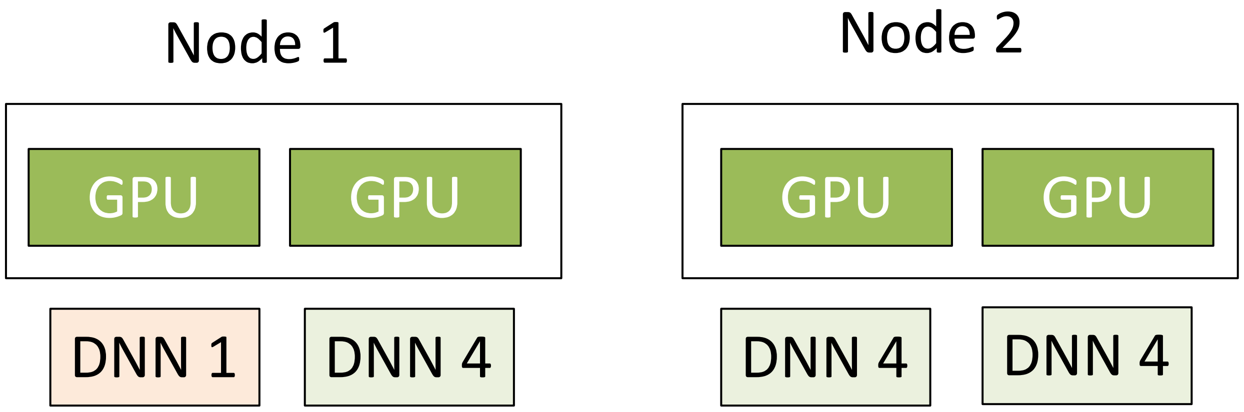
Step 2: GPU Assignment

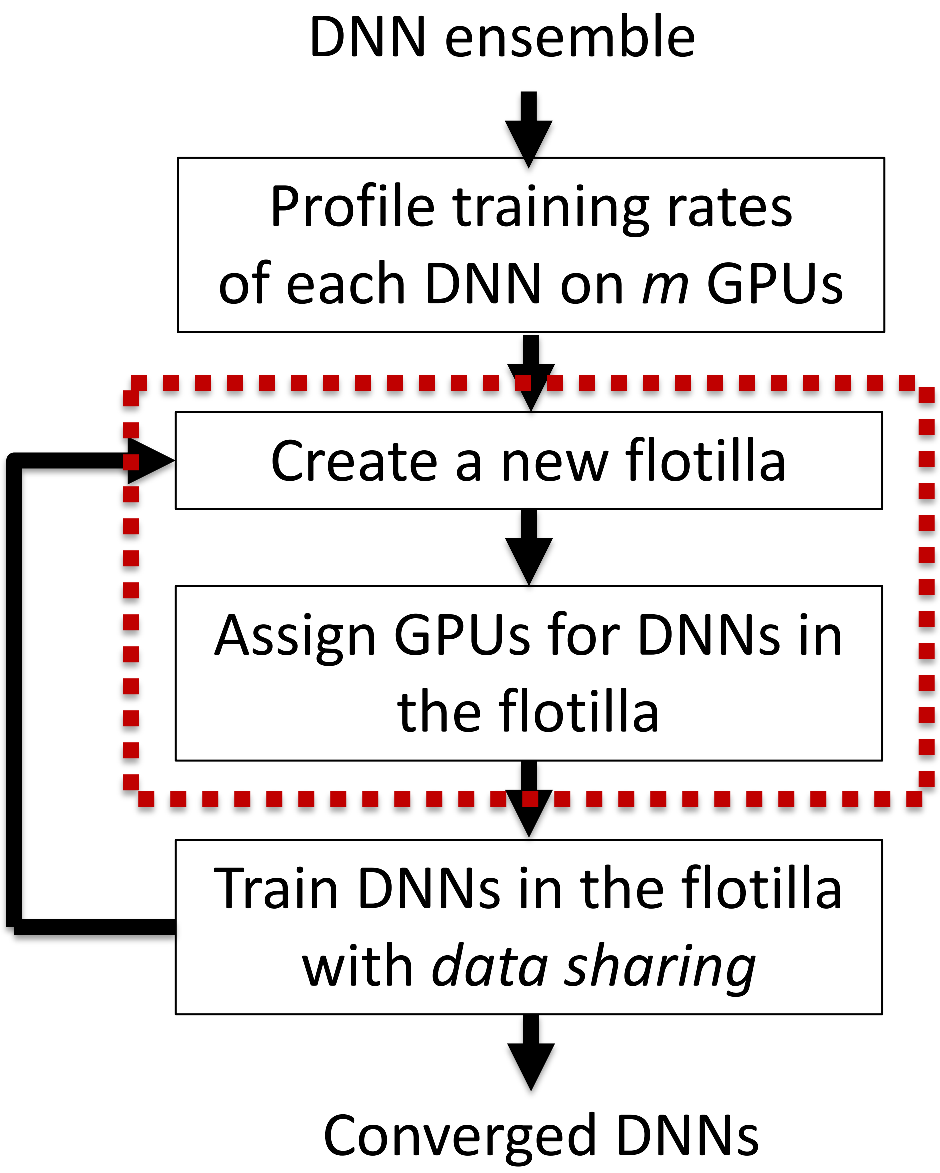


#1: When assigning multiple GPUs to a DNN, try to use GPUs in the same node.

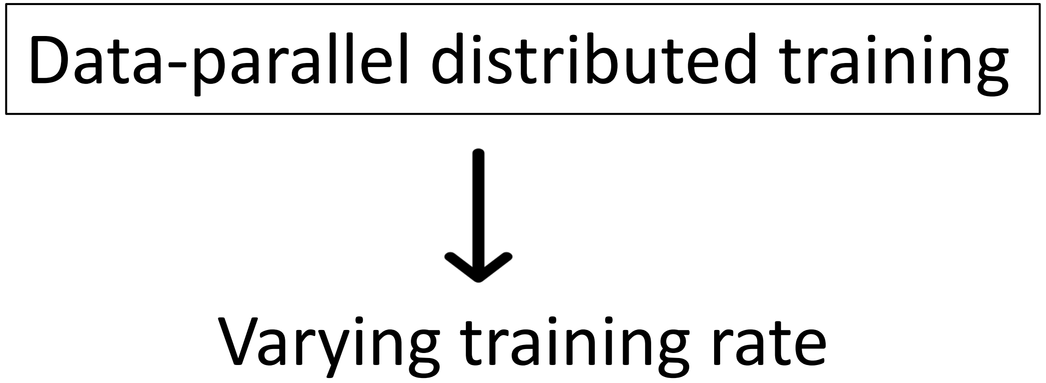
#2: Try to assign DNNs that need a smaller number of GPUs to the same node.

Reduce the variation in communication latency

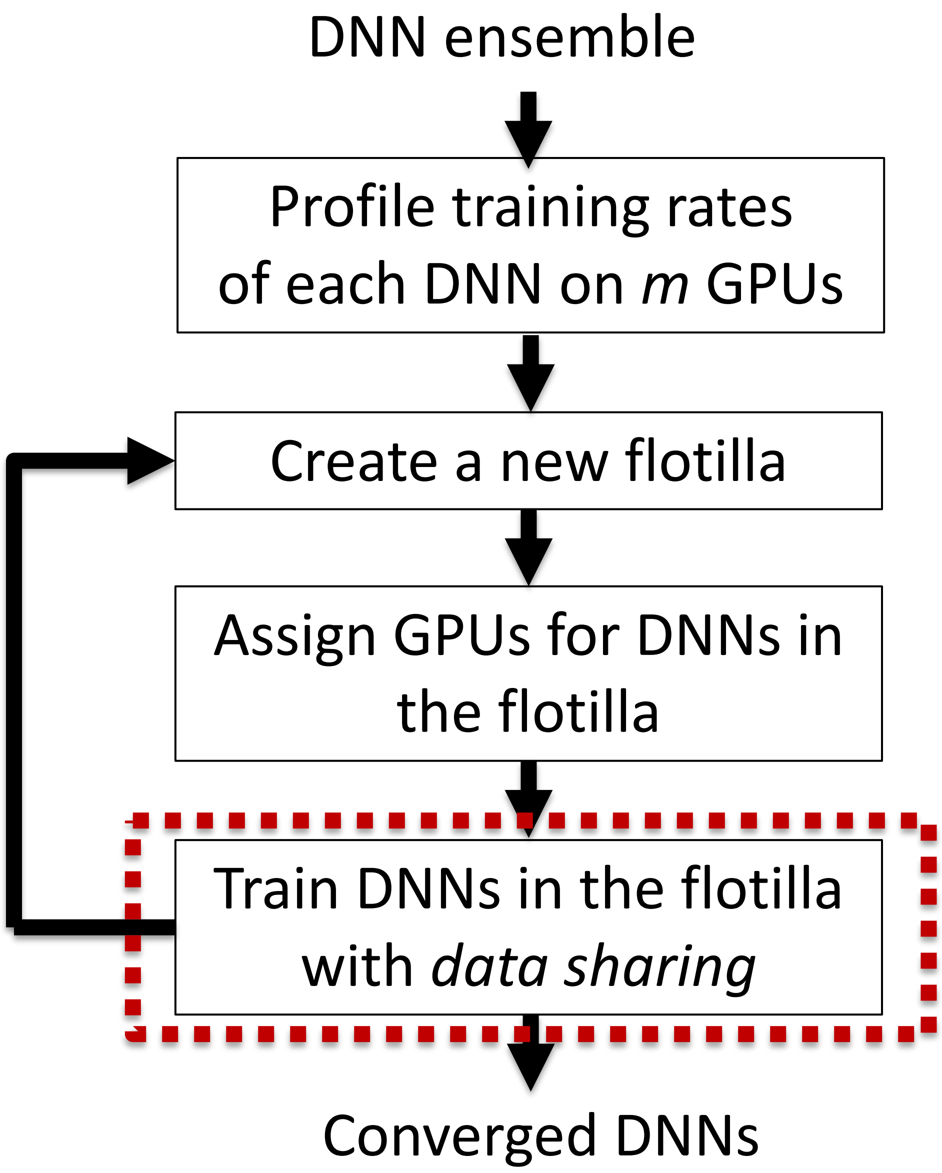




Step 1: Flotilla Creation
Step 2: GPU Assignment



Step 3: Model Training

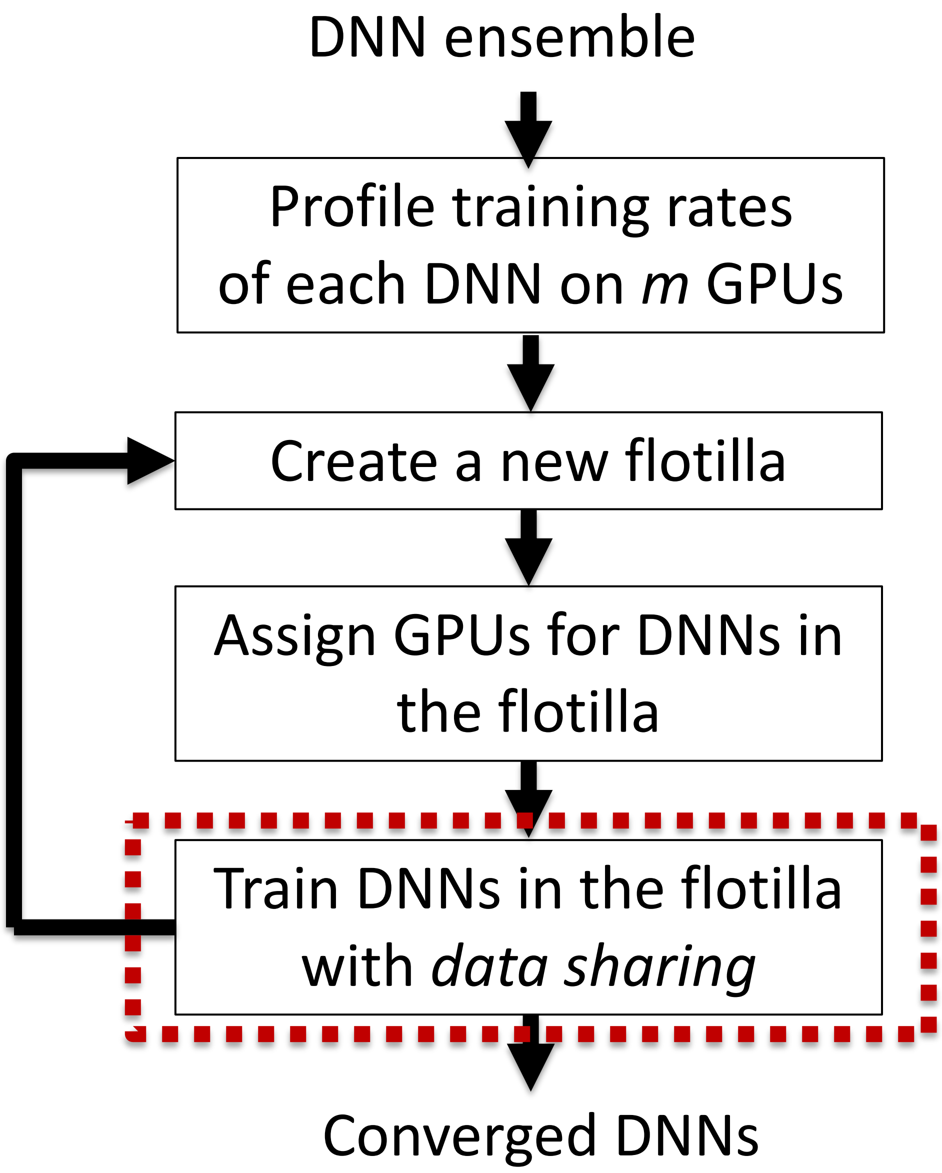


Checkpointing

↓

Varying convergence speed

Step 3: Model Training

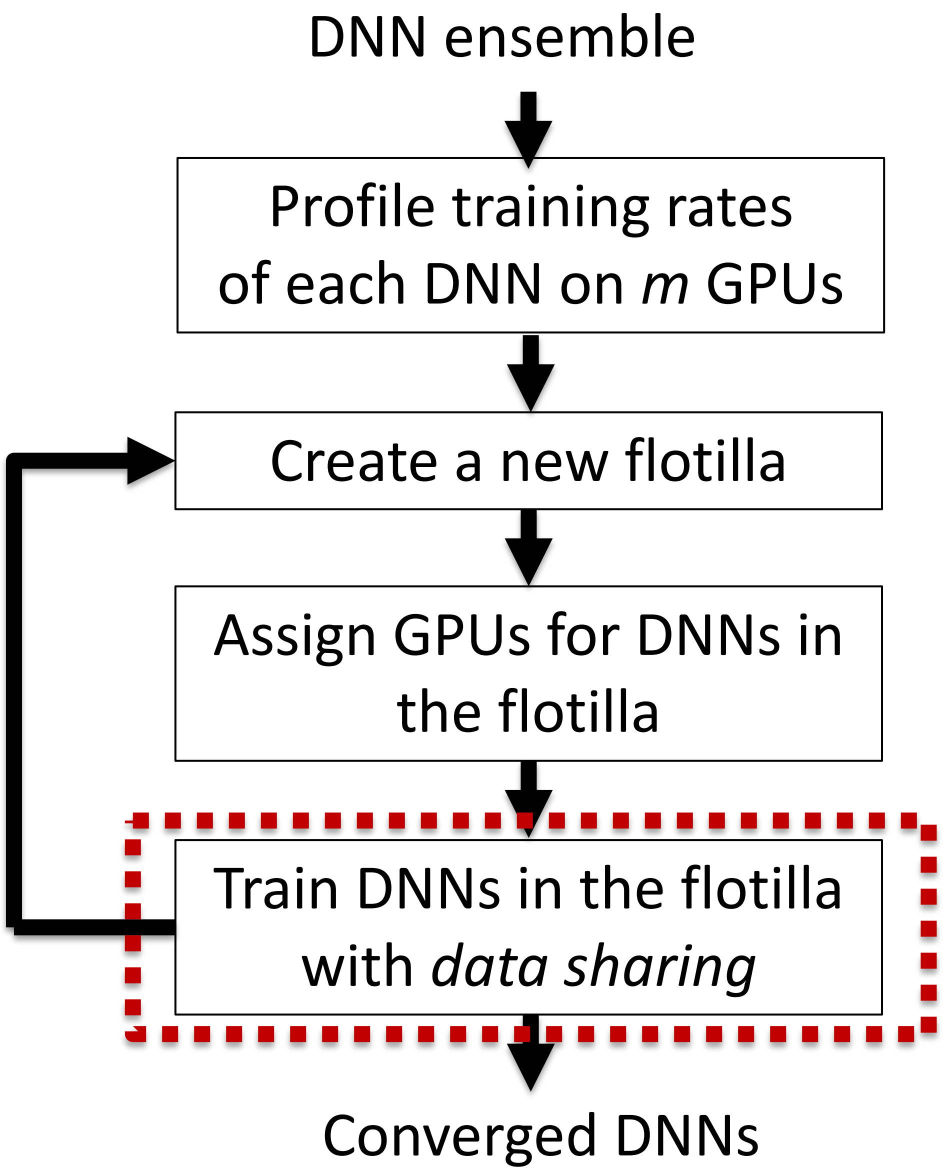


Once converged, mark as complete and release GPUs.

# GPU	1	2	3	4
~~DNN 1~~	~~100~~	~~190~~	~~270~~	~~350~~
DNN 2	80	150	220	280
DNN 3	80	150	200	240
DNN 4	40	75	100	120

Stop training the flotilla once less than 80% of GPUs remain active for training.

Step 3: Model Training



# GPU	1	2	3	4
~~DNN 1~~	~~100~~	~~190~~	~~270~~	~~350~~
DNN 2	80	150	220	280
DNN 3	80	150	200	240
DNN 4	40	75	100	120

Consider only un-converged DNNs when create the next flotilla.

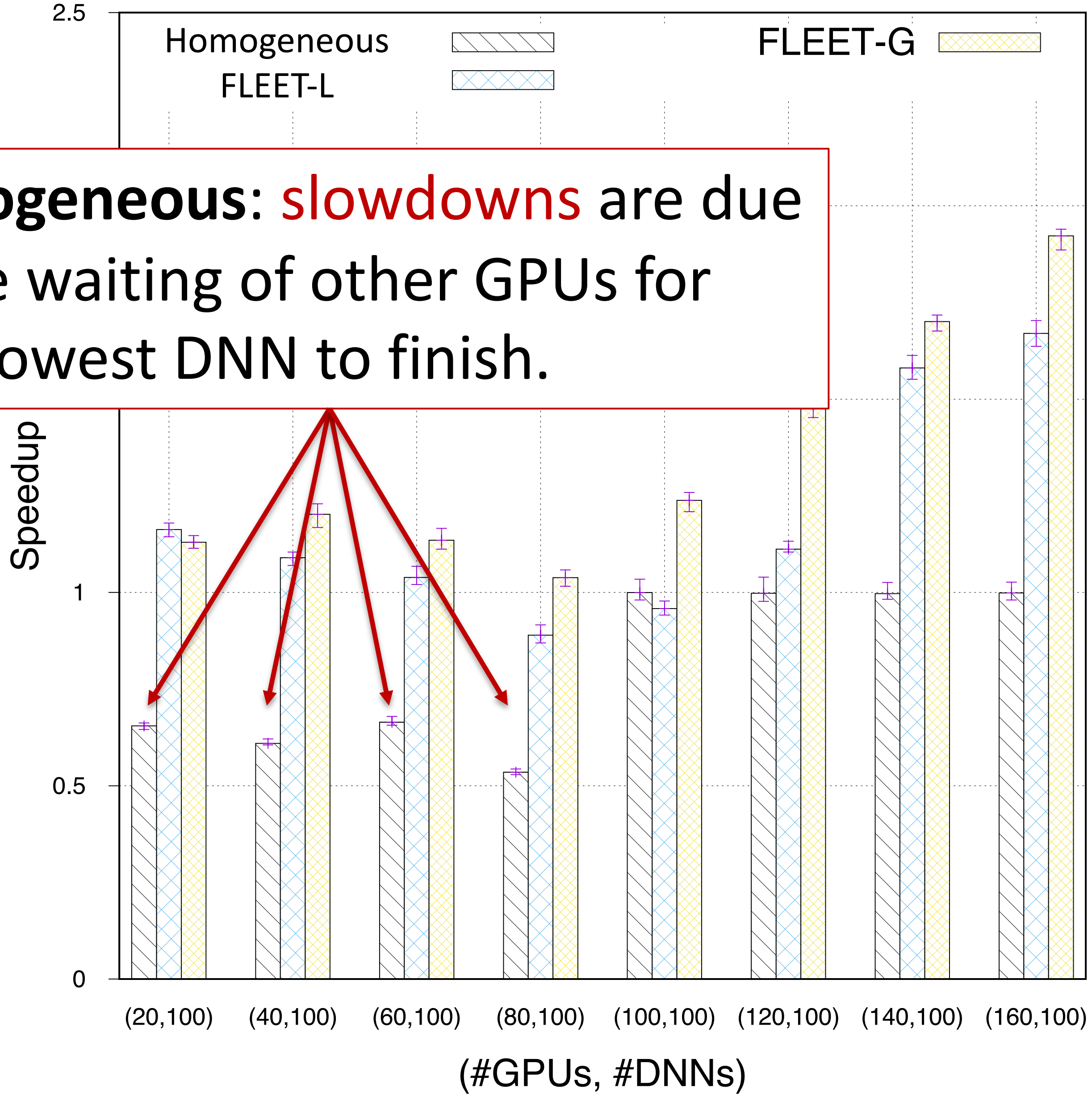
Experiment Settings

- Heterogenous ensemble
  - 100 DNNs derived from DenseNets and ResNets
  - Training rate on a single GPU: 21~176 images/sec.
- Summit-Dev@ORNL
  - 2 IBM POWER8 CPUs with 256GB DRAM
  - 4 NVIDIA Tesla P100 GPUs
- Dataset
  - Caltech256: 30K training images (240 minutes limit)

Counterparts for Comparisons

- **Baseline**
  - Train each DNN on one GPU *independently*
  - Randomly picks one yet-to-be-trained DNN whenever a GPU is free
- **Homogeneous Training** (Pittman et al., 2018)
  - Train each DNN on one GPU with *data sharing*
  - When #GPUs < #DNNs, randomly picks a subset of DNNs to train after the previous subset is done
- **FLEET-G** (*global* paradigm)
- **FLEET-L** (*local* paradigm)
  - Train remaining DNNs once some GPUs are released
  - Pick the DNNs to train by the greedy algorithm in FLEET-G

End-to-End Speedups

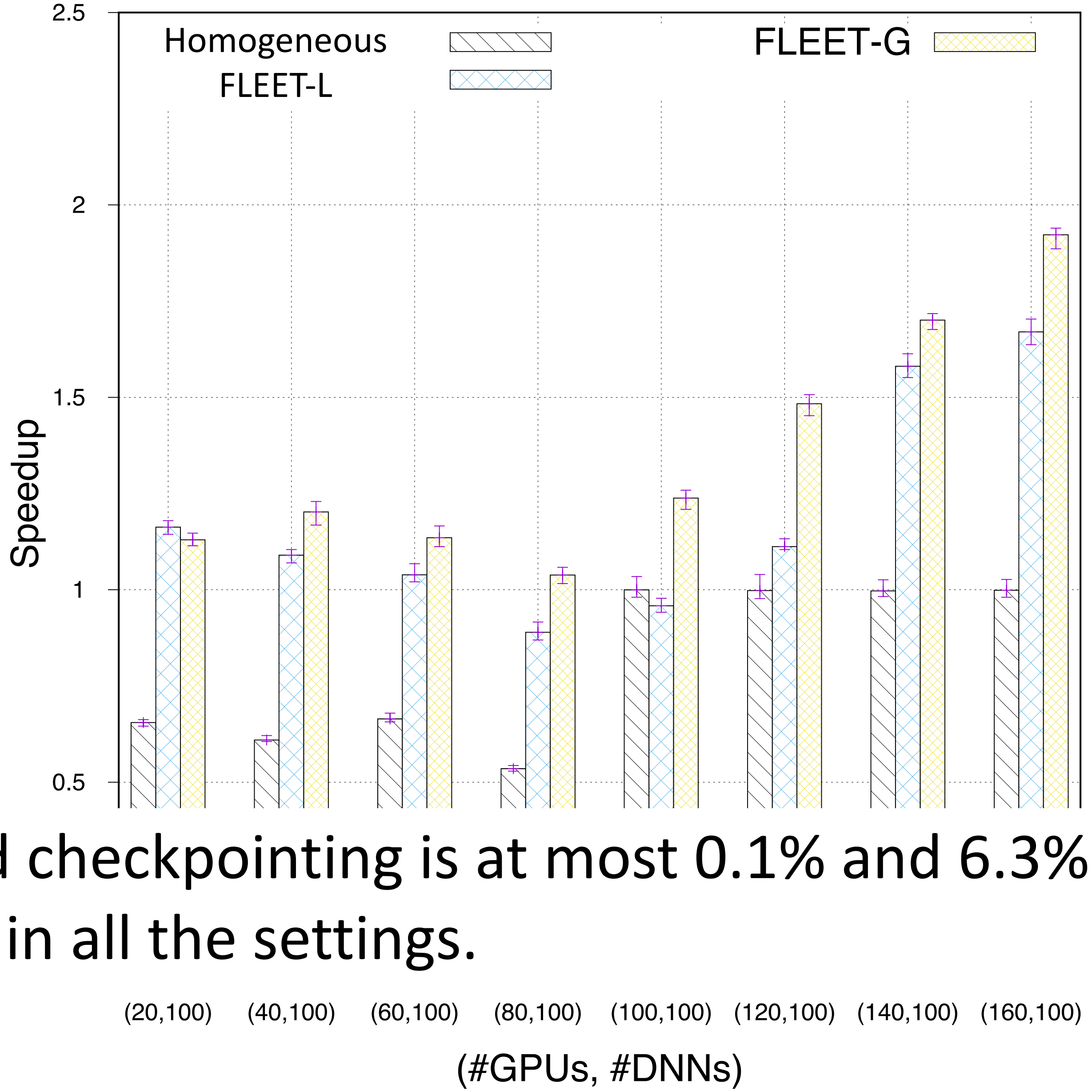


Homogeneous: slowdowns are due to the waiting of other GPUs for the slowest DNN to finish.

End-to-End Speedups

FLEET-G: the best overall performance, 1.12-1.92X speedups over the baseline.

FLEET-L: notable but smaller speedups for less favorable allocation decisions.



The overhead of scheduling and checkpointing is at most 0.1% and 6.3% of the end-to-end training time in all the settings.

Conclusions and Future Work

- Systematically explore the strategies for flexible ensemble training for a heterogenous set of DNNs.
  - Optimal resource allocation → Greedy allocation algorithm
  - Software implementation
    - Data-parallel distributed training, dynamic GPU-DNN mappings, checkpointing, data sharing

- Future work: apply FLEET to real hyperparameter tuning and neural architecture search workloads.