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Eco-FL: Adaptive Federated Learning with Efficient Edge Collaborative Pipeline Training

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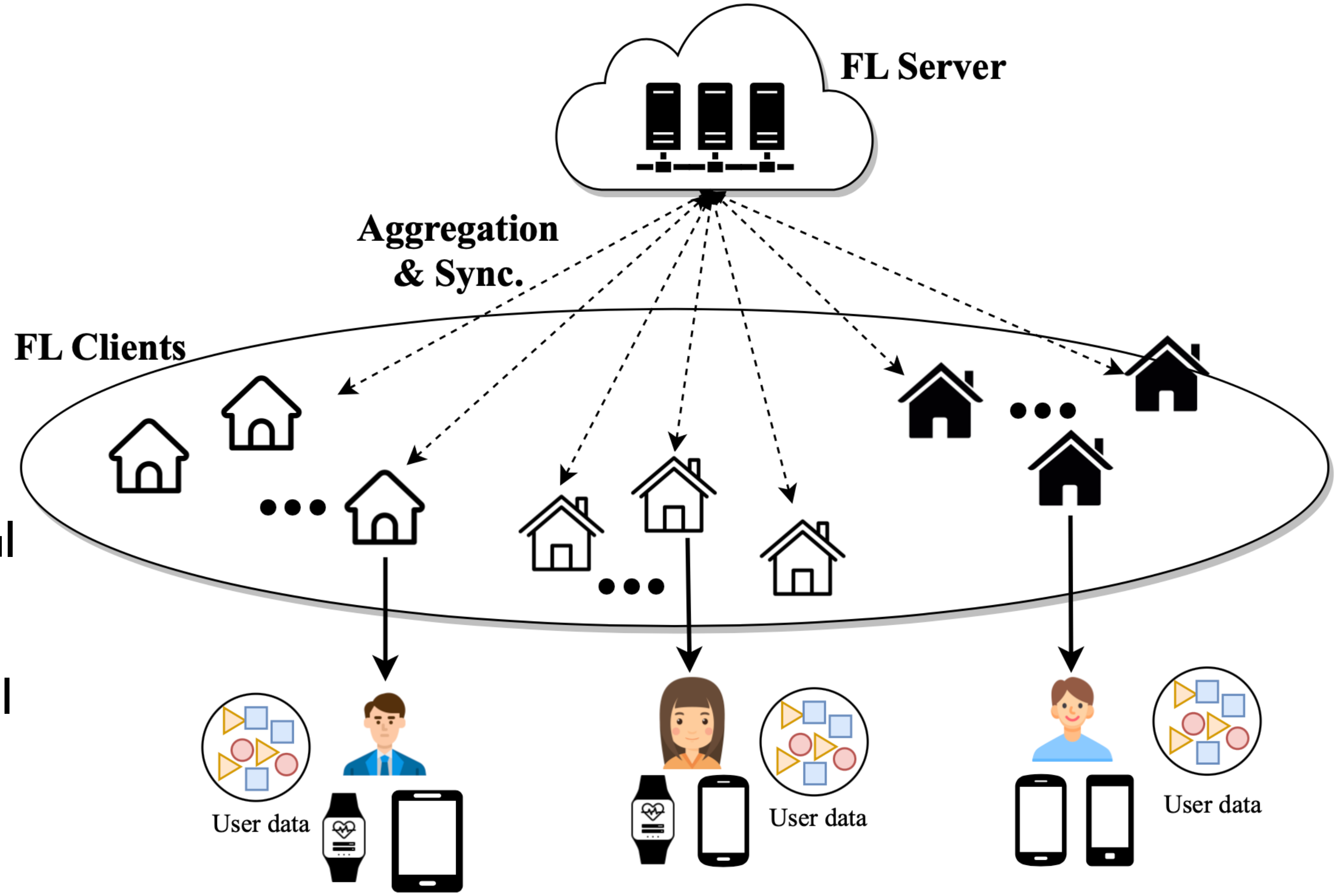
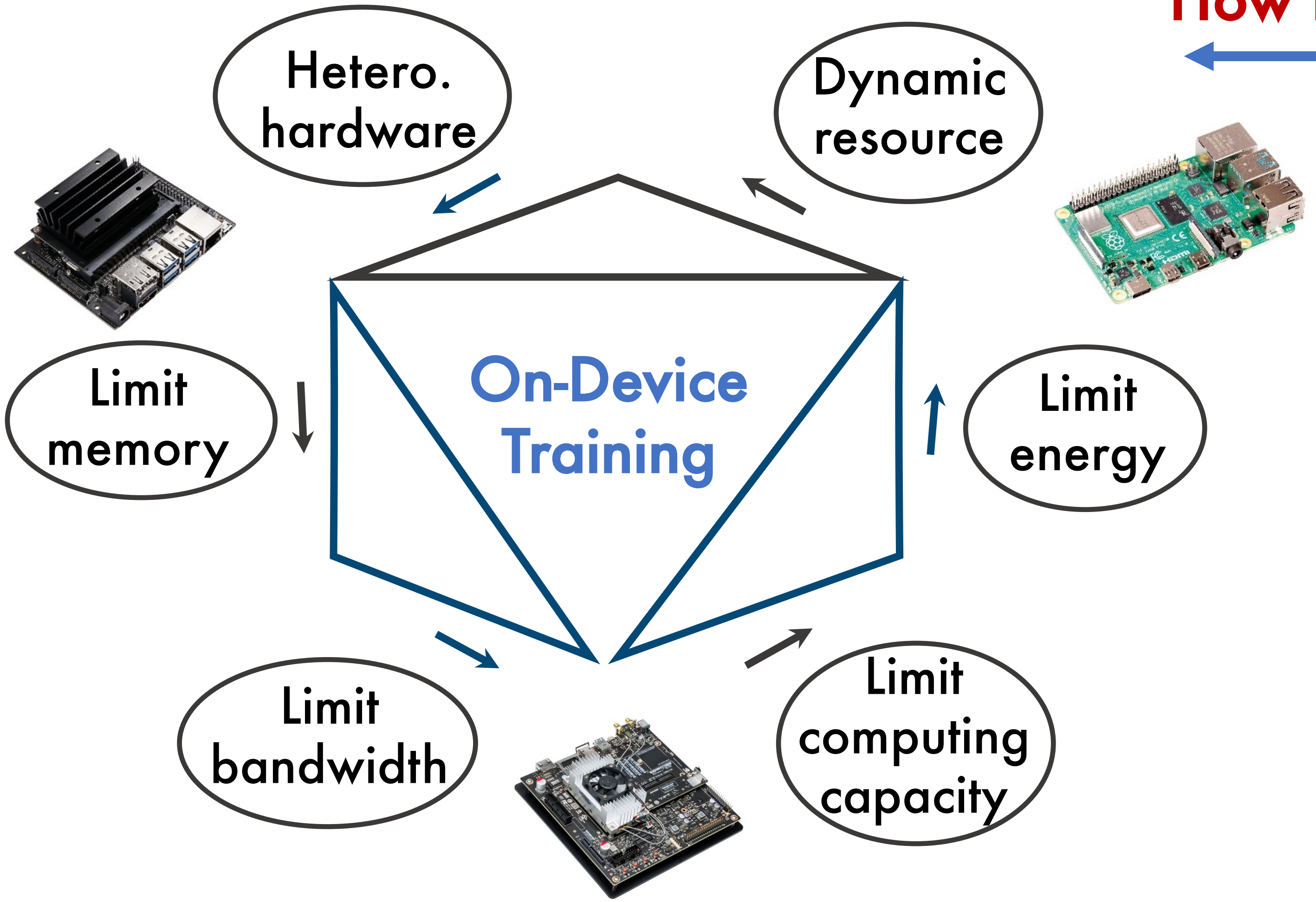
Federated Learning

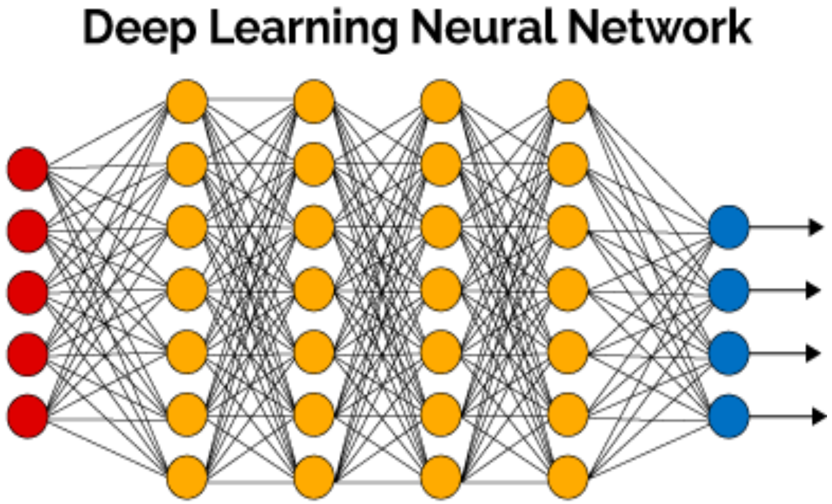
- Federated Learning workflow
  - Each client uses its local data and available IoT computing resource to learn model parameters
  - A central server aggregates parameters to update the global model
  - Periodically synchronizes global model with each client



Challenges of Training on Devices



How to train ?



- DNN Training is extremely computation-intensive and resource-demanding
- Edge devices are resource-constrained and heterogeneous

Credit: Google Image

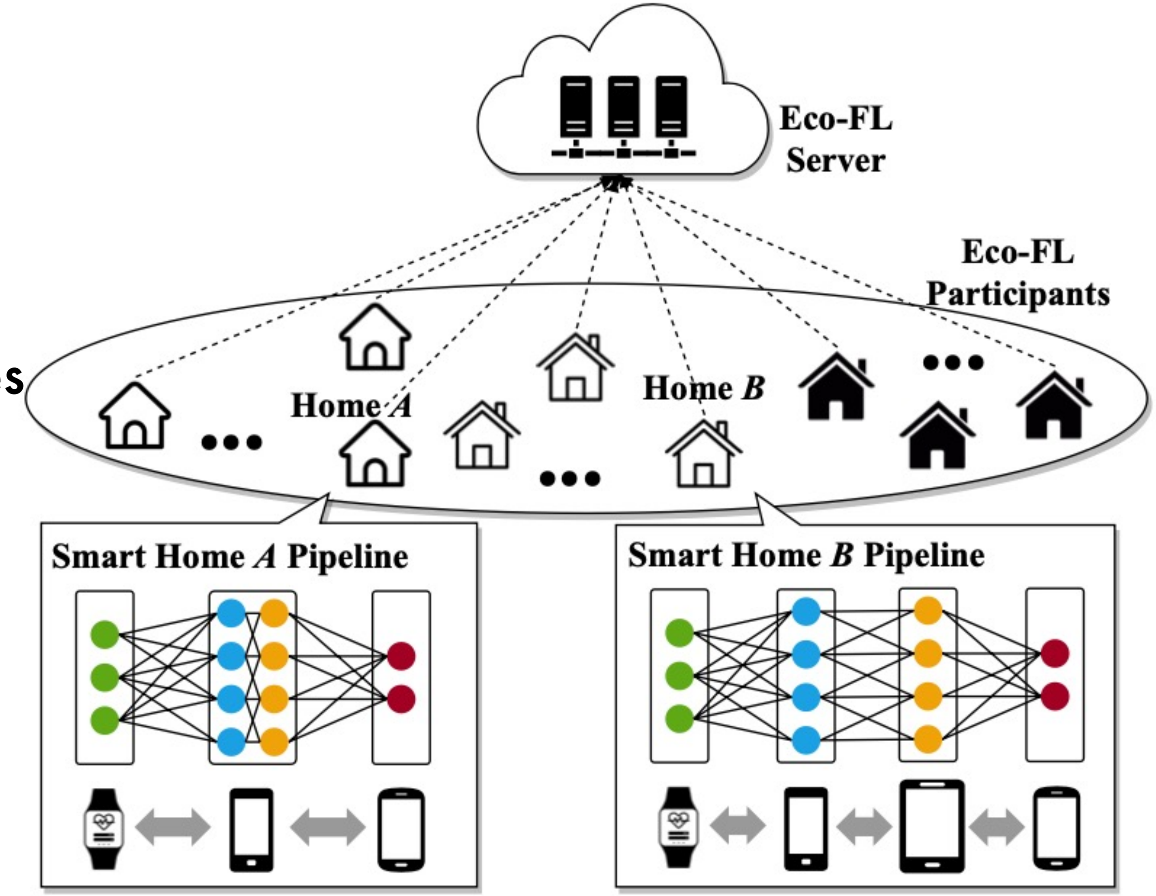
Challenges of Training on Devices

- Existing Literature:
  - Model Compression and Pruning
  - Model Quantization
  - Applying light-weight model on edge

- Drawback:
  - Defect the model test accuracy as well as FL's training convergence
  - Need to optimize specially for a particular model and is not easily expandable

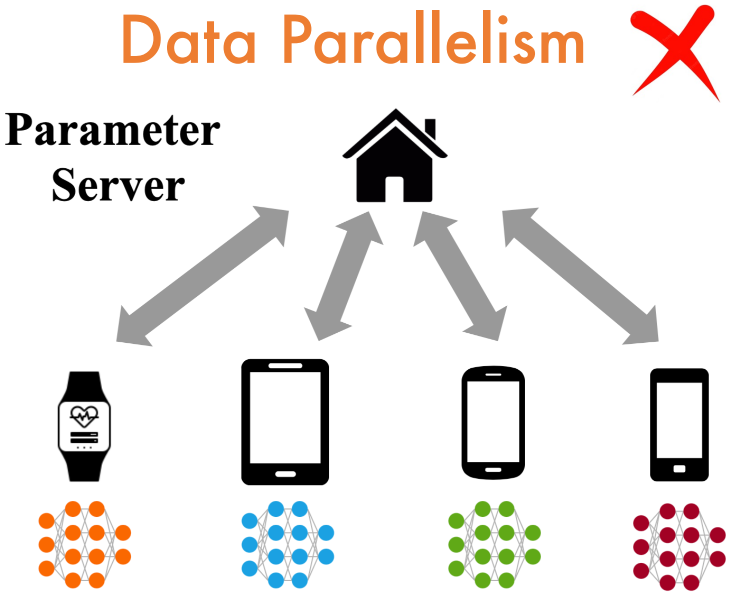
Edge Collaboration DNN Training for FL

- Issues:
  - Collaboration mechanism to orchestrate distributed edge devices
  - Dynamics computing resource of IoT devices
  - Heterogeneous computing capability of collaborated devices



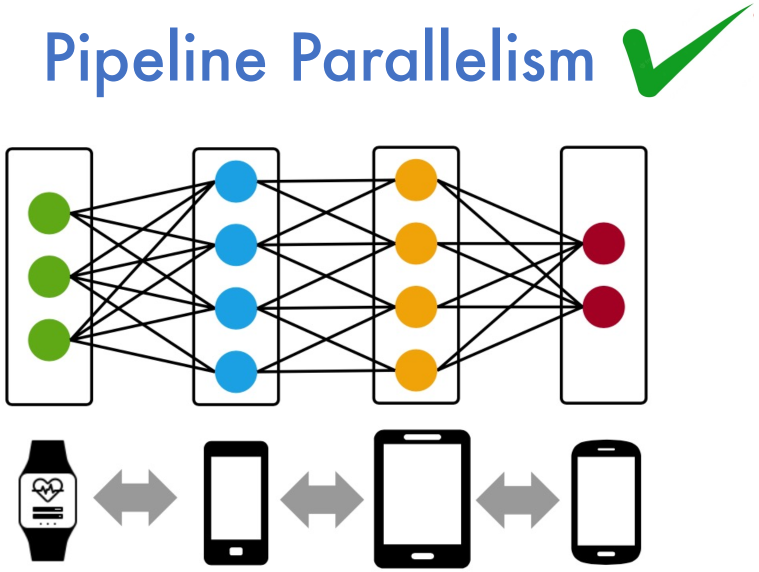
Edge Collaboration DNN Training for FL

Data Parallelism



- Each device hold a complete model, which is expensive for memory-constrained IoT devices
- Parameters transmission overhead can occupy nearly 66.3% in data parallelism training

Pipeline Parallelism

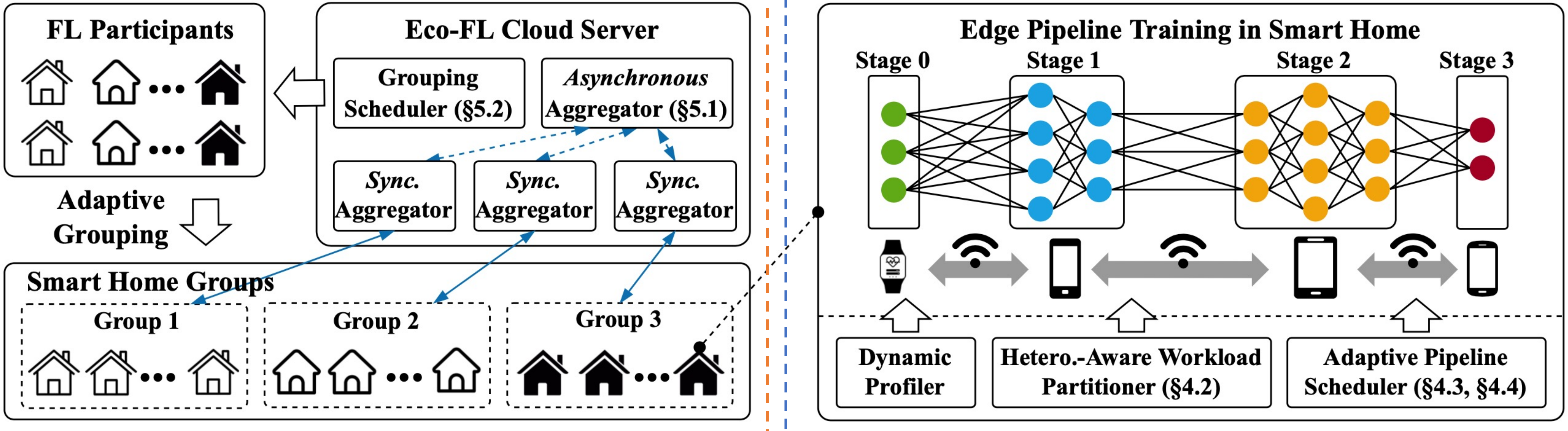


- Each device is responsible for a subset of model layers caching and computing
- Transmission overhead can be efficiently overlap by forward and backward computation

Eco-FL Framework Overview

Server-side

Client-side



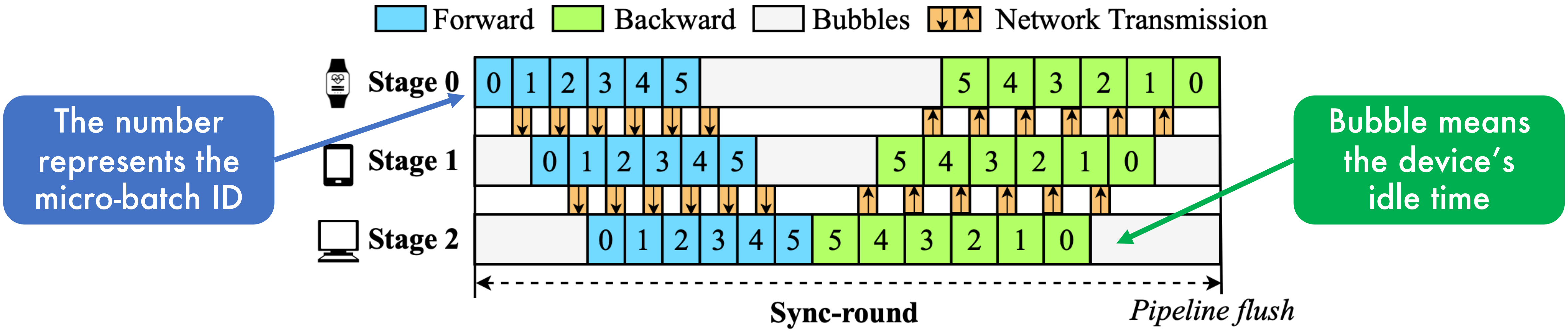
Hierarchical grouping-based FL

Pipeline edge collaboration

Collaborative Edge Training Via Pipeline Parallelism

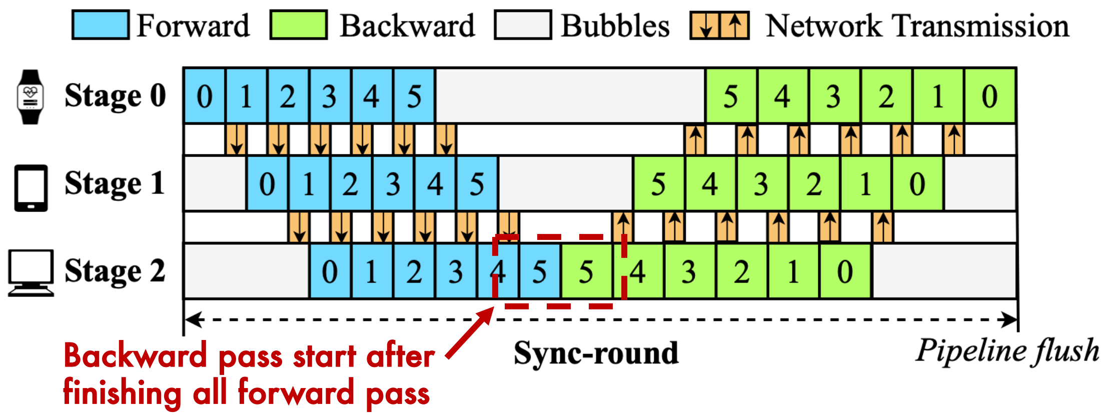
- Pipeline Parallelism Workflow

Partition DNN into stages → Split mini-batch into micro-batches → Inject micro-batches concurrently → Update stage model (Pipeline flush)



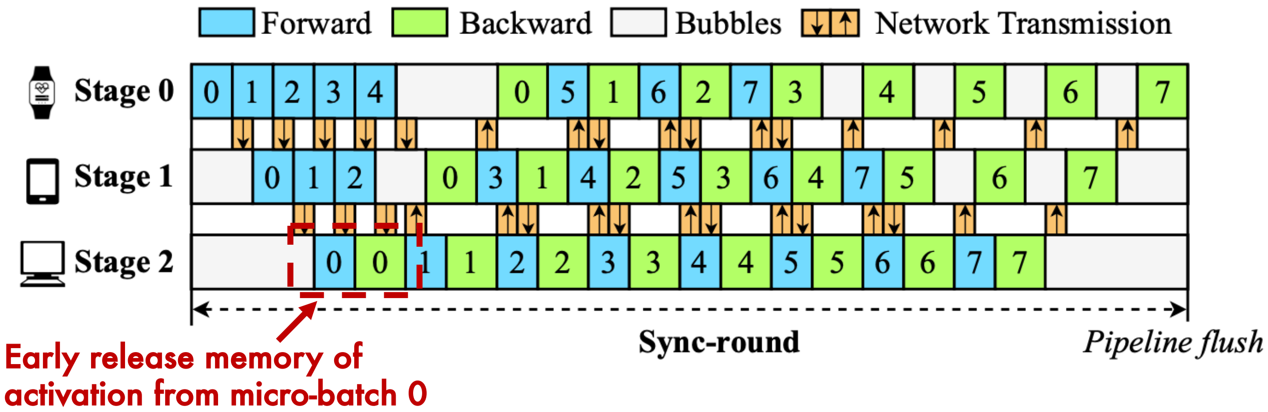
Collaborative Edge Training Via Pipeline Parallelism

Traditional Pipeline Strategy



- *B*ackward pass only start *A*fter finishing all *F*orward pass (BAF Strategy)
- Activations produced by forward tasks have to be kept for all micro-batches until backward pass begin, which is memory-unfriendly for IoT devices

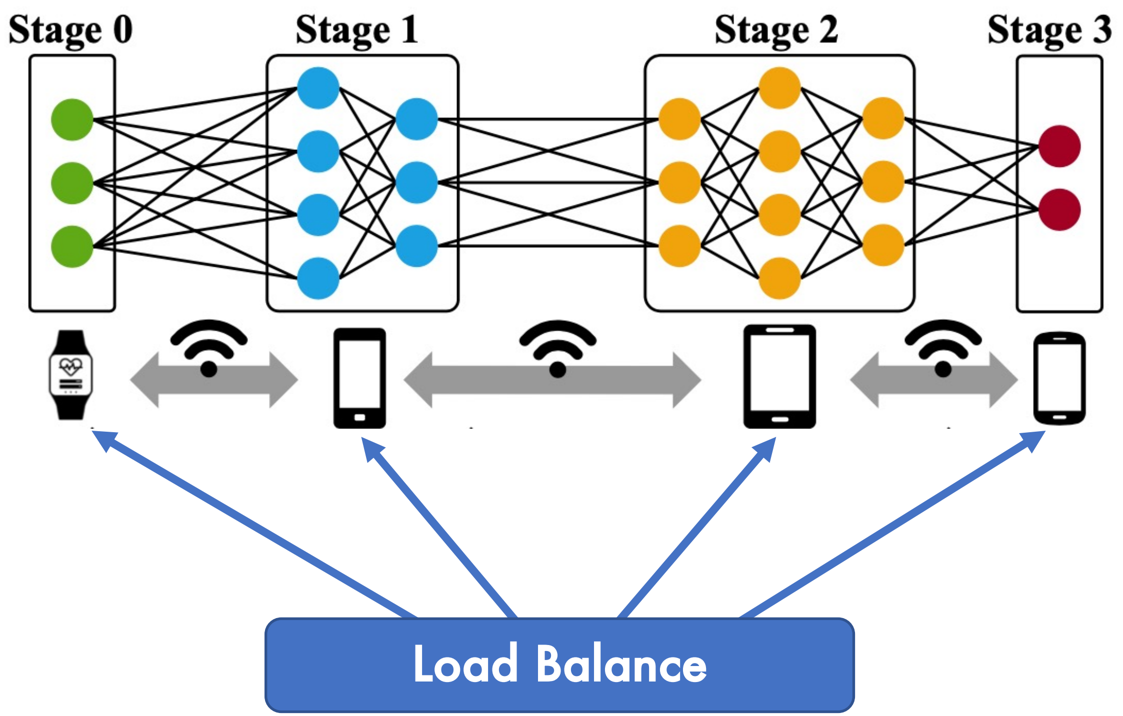
Eco-FL Resource-Efficient Pipeline Strategy



- Schedule ***one*** *F*orward pass followed by ***one*** *B*ackward pass (1F1B Strategy)
- Employ an early backward scheduling to release memory produced by forward pass for reuse
- Maintain the same throughput as BAF strategy

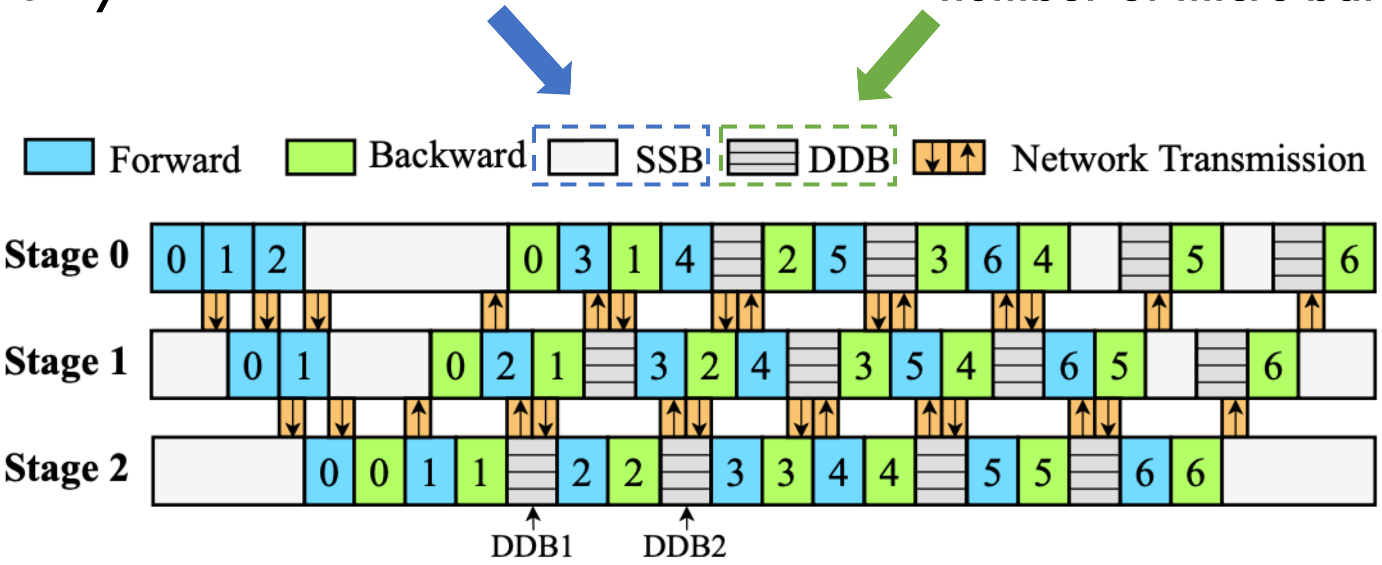
Collaborative Edge Training Via Pipeline Parallelism

- Heterogeneity-Aware Workload Partitioning
  - Step 1: Profiling
    - Monitor the computation time across forward pass and backward pass on heterogeneous IoT devices
    - Collect layer message of DNN model
  - Step 2: Workload Partitioning:
    - Global throughput of the pipeline is determined by the execution time of slowest stage (lagger)
    - Partition the model into balanced stages with dynamic programming algorithm



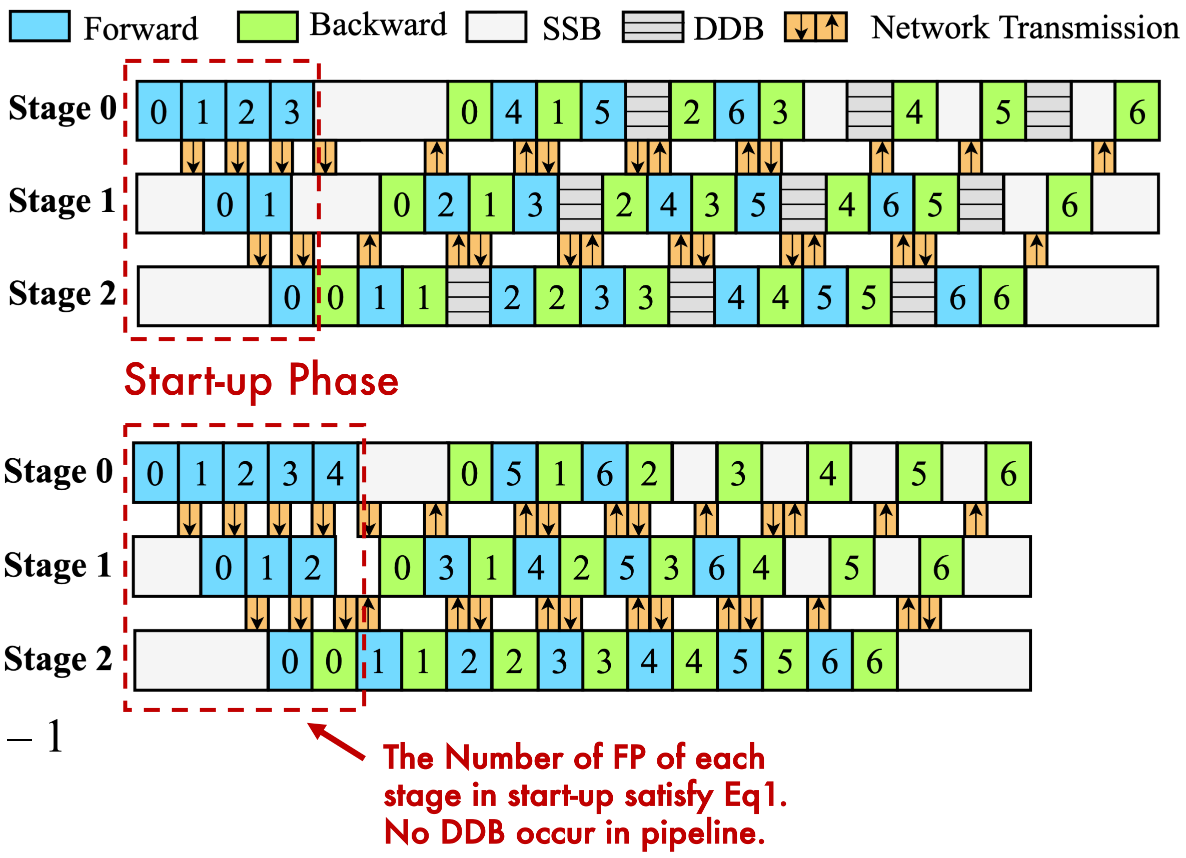
Collaborative Edge Training Via Pipeline Parallelism

- Pipeline bubbles analysis
  - Synchronous Static Bubble (SSB)
    - Caused by the periodic pipeline flush, inevitable in synchronous strategy
    - Can be minimized by increasing the number of micro-batches injected concurrently
  - Data Dependency Bubble (DDB)
    - Caused by the data dependency of micro-batches in pipeline training.
    - The occurrence of DDB is periodic and can not be eliminated by increasing the number of micro-batches



Collaborative Edge Training Via Pipeline Parallelism

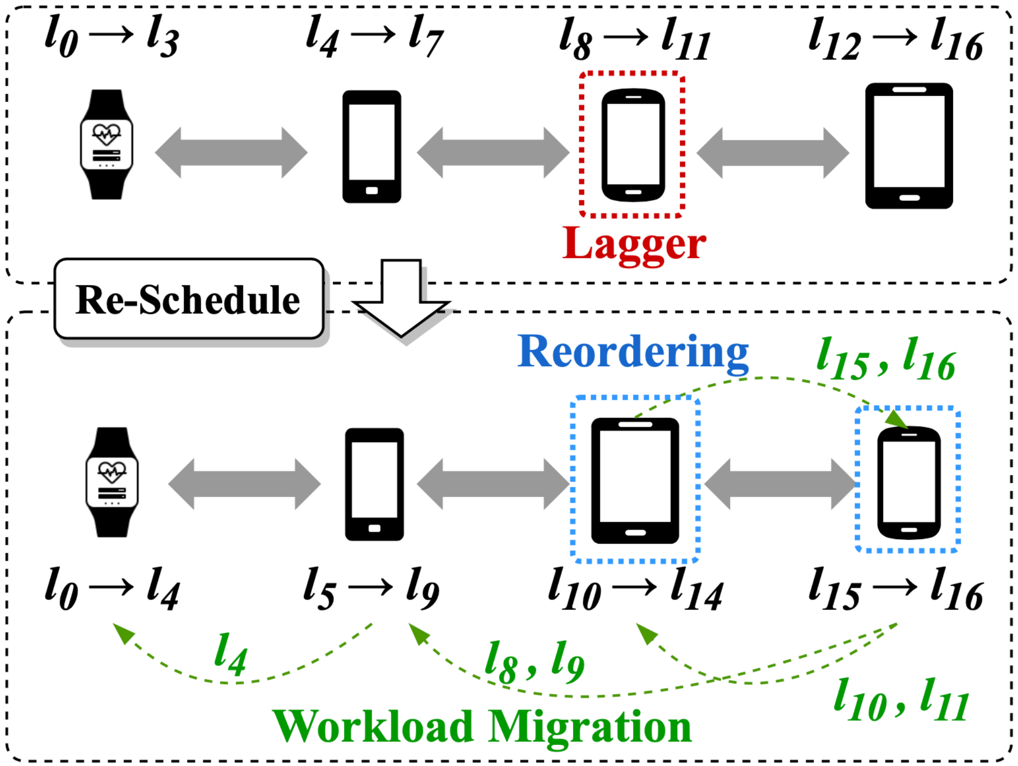
- Trade off between training throughput and peak memory usage
  - DDB is determined by the the number of forward pass (FP) in start-up phase
  - If the number of FP in start-up phase too small, DDB will occur. But if too many FP reside concurrently in stages, it will cause memory pressure to IoT devices.



- Best micro-batch scheduling strategy
  - **Eq1:** # of FP in start-up = 2(# of stages – stage index) – 1
  - Avoid the occurrence of DDB while minimizing memory pressure of each stage

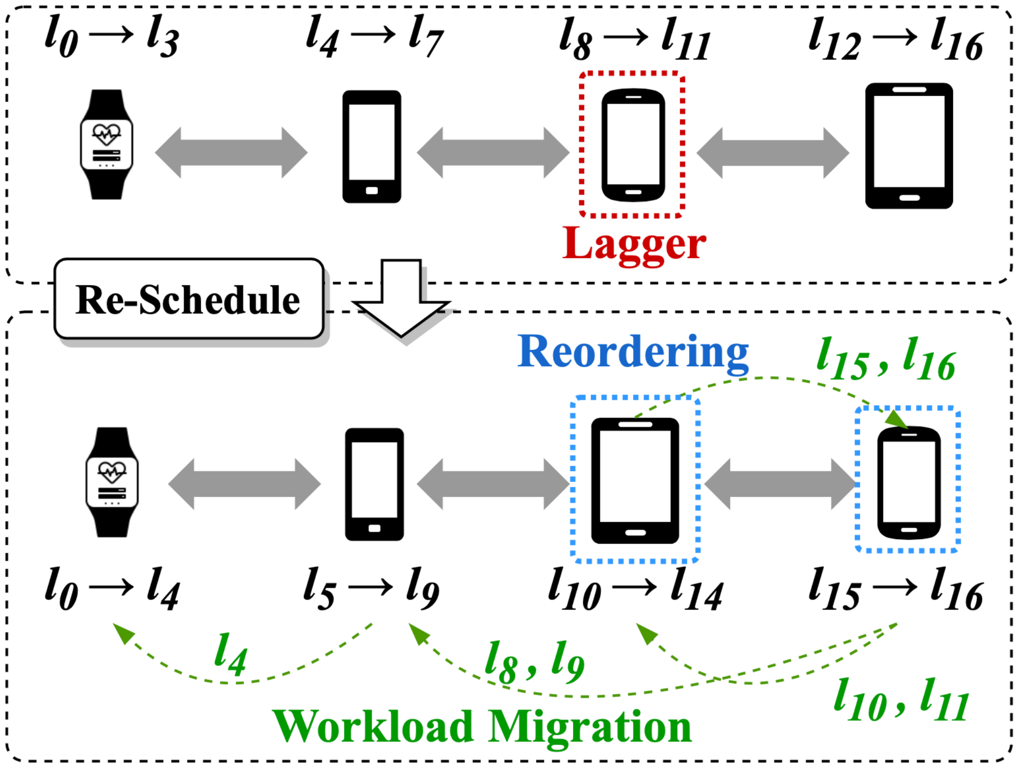
Collaborative Edge Training Via Pipeline Parallelism

- Issue: Dynamic edge resources
  - IoT devices usually have high variation in available computing capability and memory resources
  - The maximum throughput of the pipeline is greatly determined by the lagger



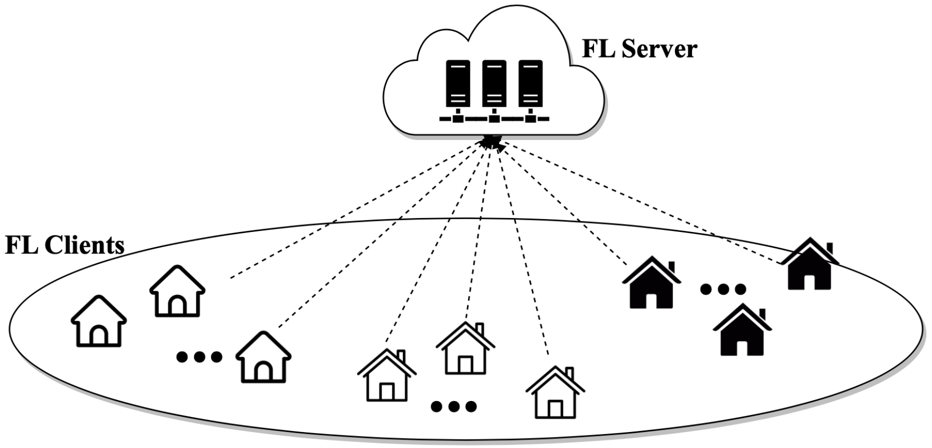
Collaborative Edge Training Via Pipeline Parallelism

- Issue: Dynamic edge resources
  - IoT devices usually have high variation in available computing capability and memory resources
  - The maximum throughput of the pipeline is greatly determined by the lagger
- Solution: Adaptive workload migration
  - Training worker will periodically report the execution time of FP and BP
  - If there is a large deviation between the current and historical execution time of any device, pipeline will adaptively self-rebalance and migrate workload according to new scheduling.



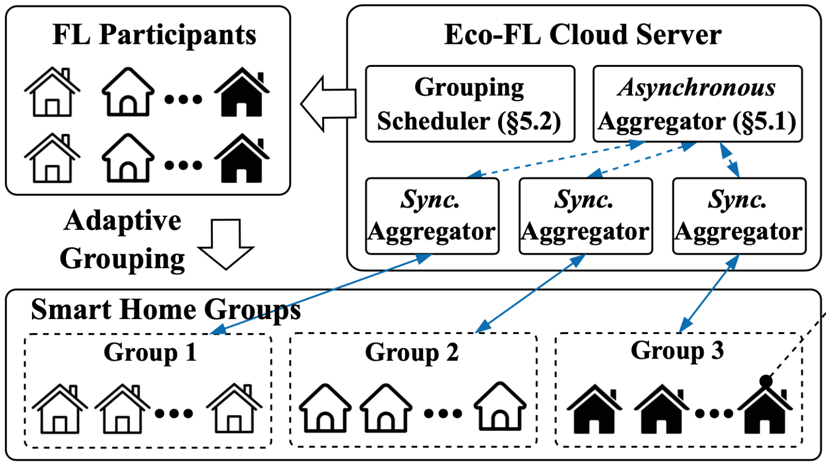
Grouping-based Hierarchical FL Aggregations

Traditional Sync. & Async. FL Architecture



- Sync. FL:
  - ✔ Achieve high training performance
  - ✘ The slowest client (straggler) can significantly prolong the training time
- Async. FL:
  - ✔ Alleviate the straggler issue
  - ✘ Sacrifice accuracy and convergence speed

Eco-FL Hierarchical Architecture

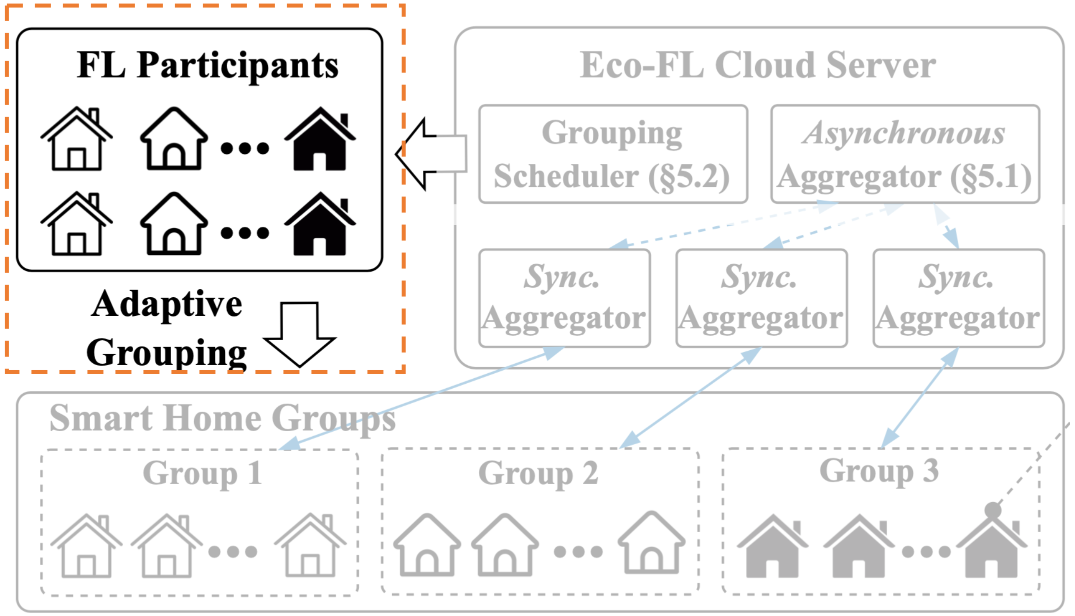


- The available trusted devices that each smart home can collaborate with usually vary, which causes severe straggler issue
- Hybrid Hierarchical FL combine the best of both Sync. and Async. mechanisms, while efficiently alleviate straggler issue.

Grouping-based Hierarchical FL Aggregations

Adaptive Client Grouping → Intra-group Sync. Aggregation → Inter-group Async. Aggregation

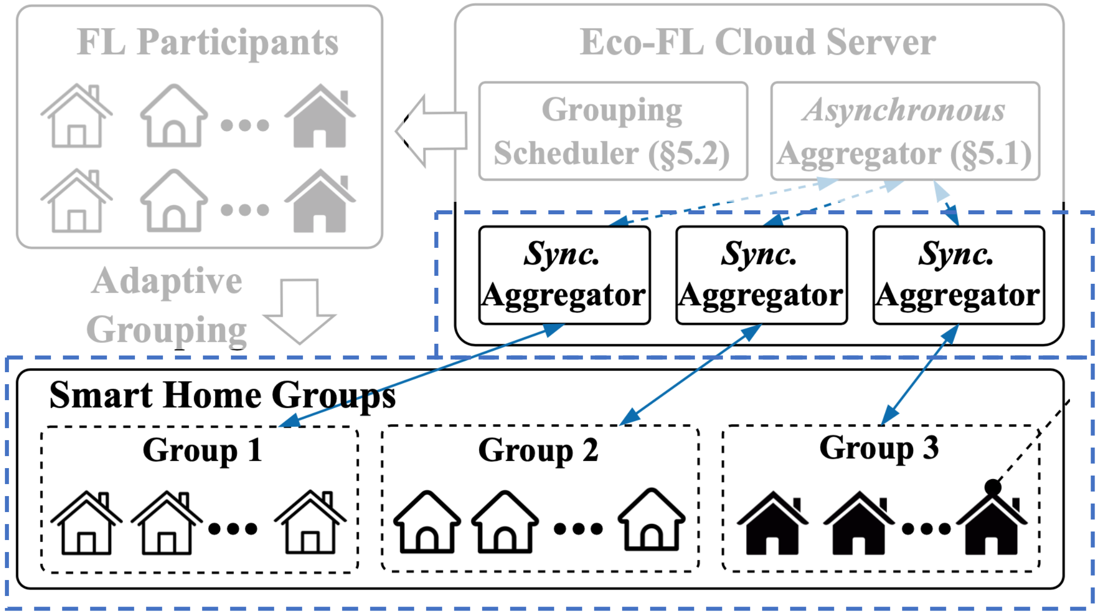
- Adaptive Client Grouping:
  - Group smart homes according to their training performance and data distribution



Grouping-based Hierarchical FL Aggregations

Adaptive Client Grouping → Intra-group Sync. Aggregation → Inter-group Async. Aggregation

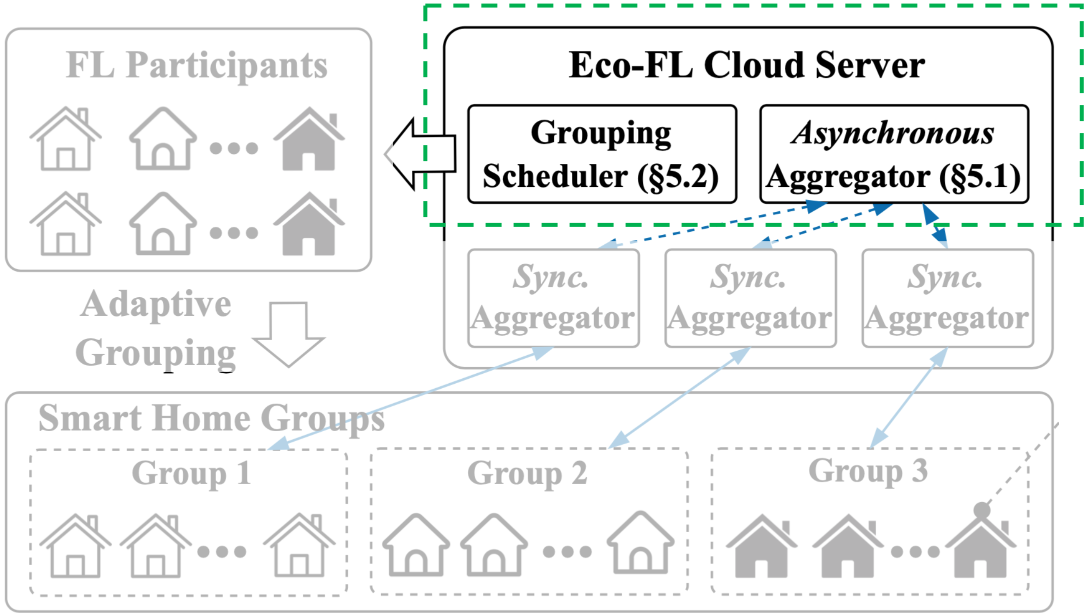
- Adaptive Client Grouping:
  - Group smart homes according to their training performance and data distribution
- Intra-group Synchronous Aggregation:
  - Synchronous aggregation is applied to aggregate model updates from the clients with similar response latency within a same group



Grouping-based Hierarchical FL Aggregations

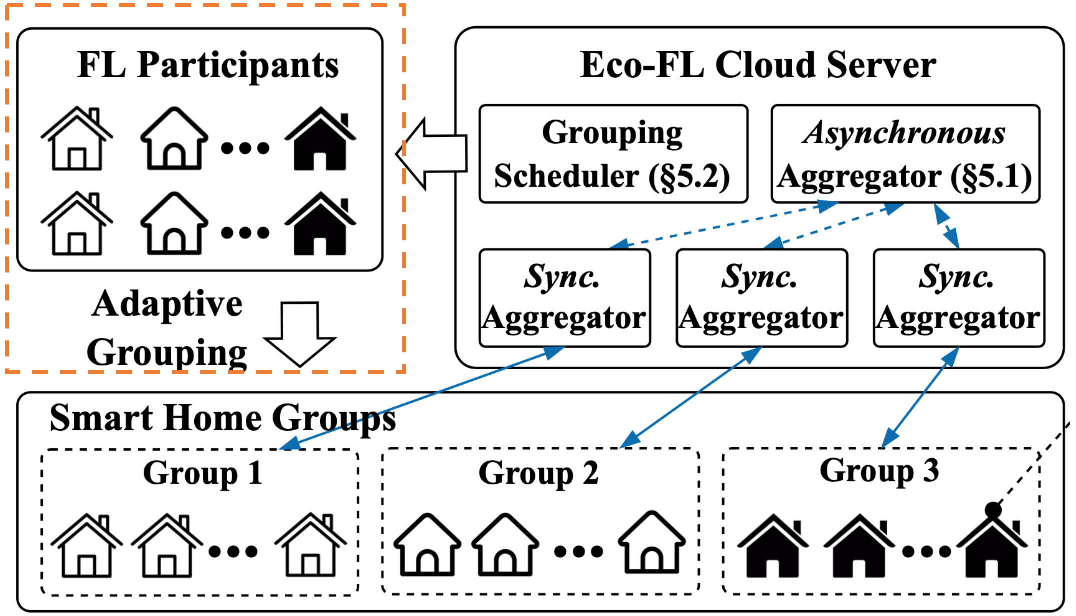
Adaptive Client Grouping → Intra-group Sync. Aggregation → Inter-group Async. Aggregation

- Adaptive Client Grouping:
  - Group smart homes according to their training performance and data distribution
- Intra-group Synchronous Aggregation:
  - Synchronous aggregation is applied to aggregate model updates from the clients with similar response latency within a same group
- Inter-group Asynchronous Aggregation:
  - Asynchronous aggregation is made for global model aggregation among different groups



Grouping-based Hierarchical FL Aggregations

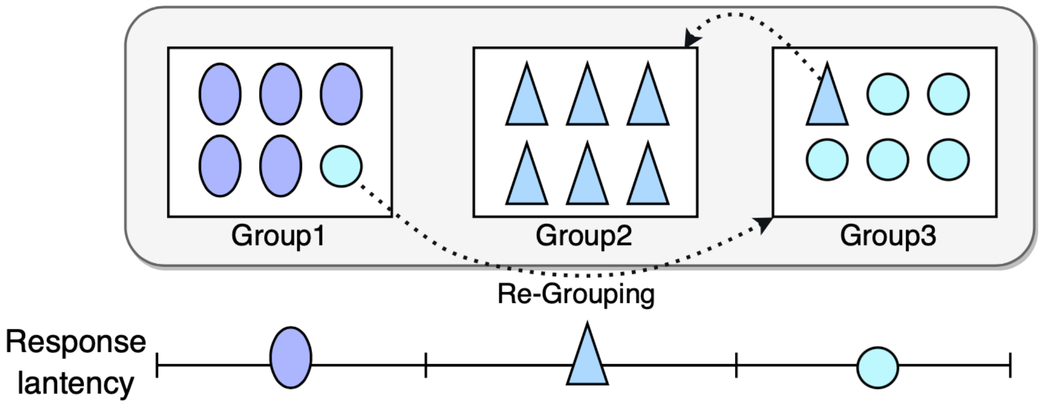
- Heterogeneity-aware Client Grouping
  - System heterogeneity: Stragglers will prolong the synchronous training time intra-group
  - Data heterogeneity: Non-IID characteristics can harm the convergence of model training during synchronous process intra-group



- Grouping Target:
  - Let the response latency of the members in the group be as close as possible while having an associated data distribution as close as possible to the I.I.D. distribution

Grouping-based Hierarchical FL Aggregations

- Dynamic Client Re-grouping
  - The response latency of each client can be varying occasionally due to the changes in its collaborative device resources, which can disable the static grouping method
  - Eco-FL server will monitor each client in run-time and dynamically re-group client according to their real-time response latency



Algorithm 1: Adaptive Grouping Process

Process `Eco-FLServer()`:
    Collect and monitor response latency of each client;
    if *Client* n *in group* g *satisfy* $|L^g - L_n| > RT^g$ **then**
        `Regroup`(n);
    end
Function `Regroup`(n):
    $\text{MinCost} \leftarrow +\infty$, $t \leftarrow -1$;
    for $g \in \{0, 1, ..., |\mathcal{G}| - 1\}$ **do**
        if $COST_n^g < MinCost$ *and* $|L^g - L_n| \leq RT^g$ **then**
            $t \leftarrow g$;
            $\text{MinCost} \leftarrow \text{COST}_n^g$;
        end
    end
    if $t \neq -1$ **then**
        Move client n to group t;
    else
        Drop out client n until its response latency L_n meets the threshold range of any group;
    end

Evaluation

- Experimental Setting

Federated Learning

- Models:
  - CNN with two 5x5 convolution layers
- Baselines:
  - FedAvg, FedAsync, FedAT, Astraea
- Datasets:
  - Cifar10, MNIST, Fashion-MNIST
- Testbed:
  - Virtual machine instance (48 vCPUs and 64GB memory)
  - Use Docker to deploy FL server and clients. Each client gets assigned 2 vCPU cores

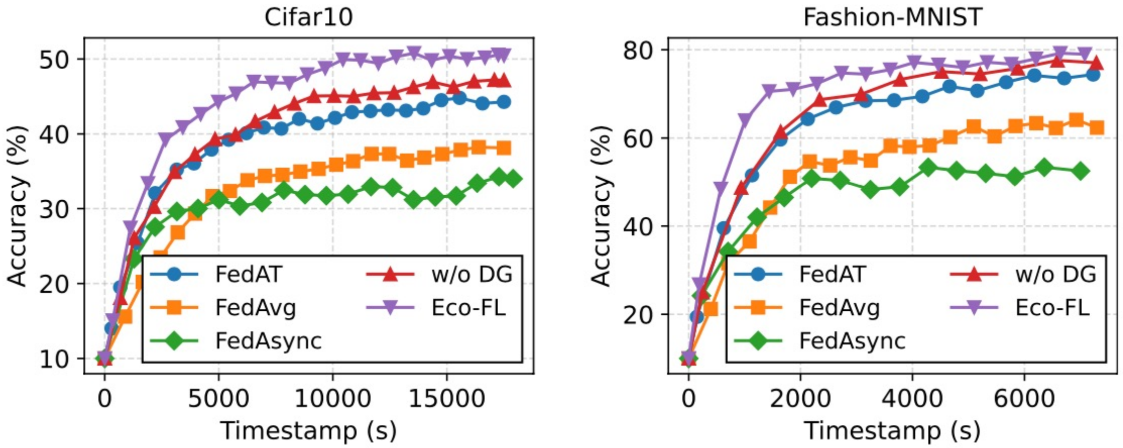
Pipeline Training

- Models:
  - EfficientNet, MobileNetv2
- Baselines:
  - PipeDream, Gpipe, Single device
- Testbed:

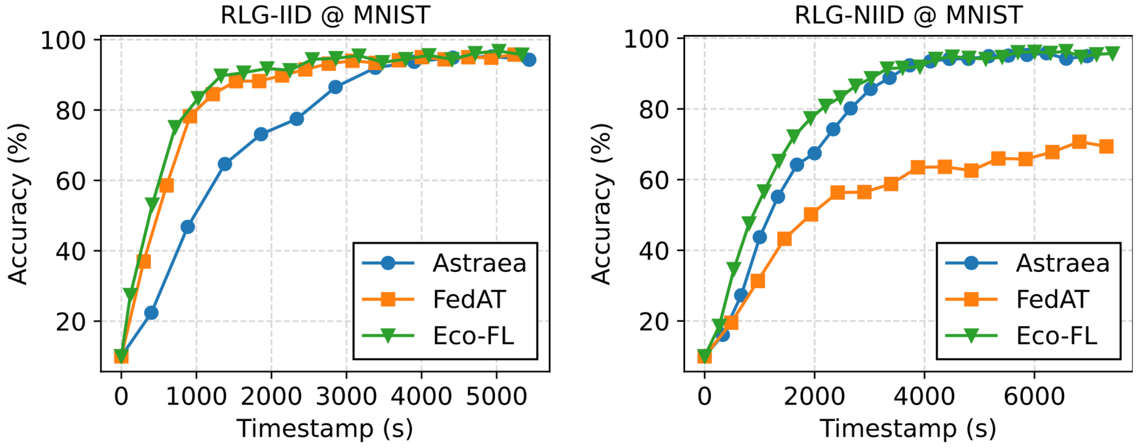
Hardware	Power Mode	GPU Max Frequency	Memory	Network Bandwidth
Jetson Nano	5W (L) 10W (H)	640MHz 921.6MHz	4GB	100Mbps
Jetson TX2	Max-Q Max-N	850MHz 1.3GHz	8GB	100Mbps

Evaluation

- Federated Learning Performance
  - Training performance
    - Eco-FL hierarchical architecture outperforms the baselines with faster convergence and higher achieved accuracy
    - Eco-FL with the adaptive scheduler can still maintain a high performance under the IoT environment with dynamic nature
  - Heterogeneity-aware client grouping
    - FedAT: Group clients only based on response latency
    - Astraea: Grouping clients only based on data distribution
    - Eco-FL heterogeneity-aware grouping method outperform both FedAT and Astraea up to 26.3% on testing accuracy



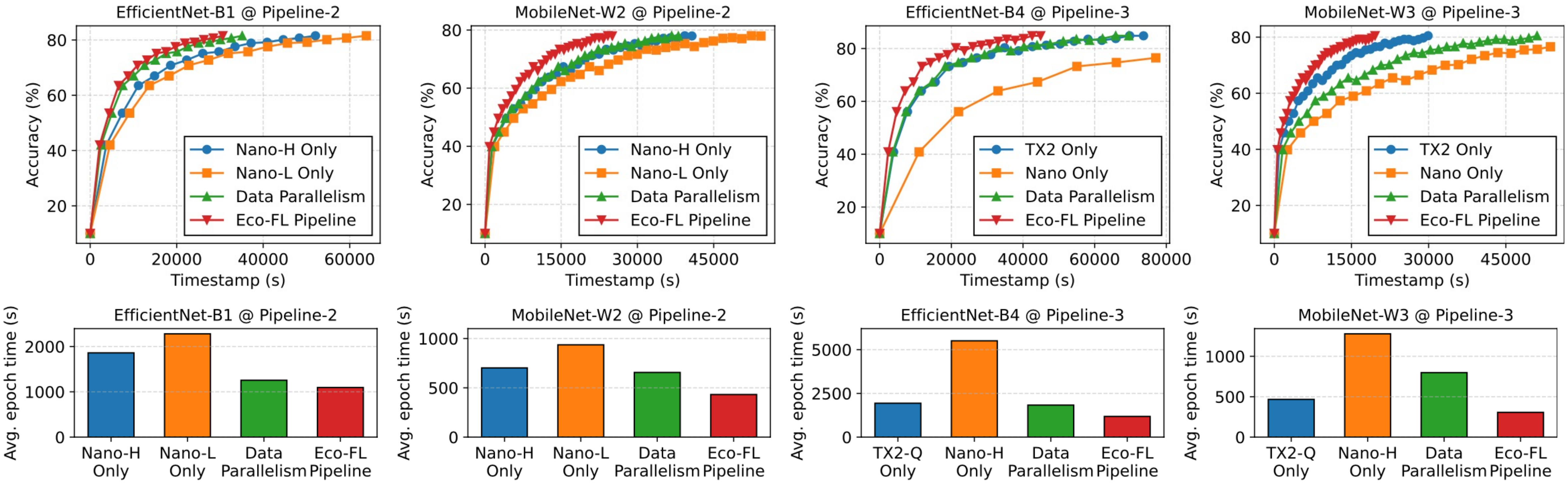
Training performance with different datasets



Effectiveness of heterogeneity-aware client grouping

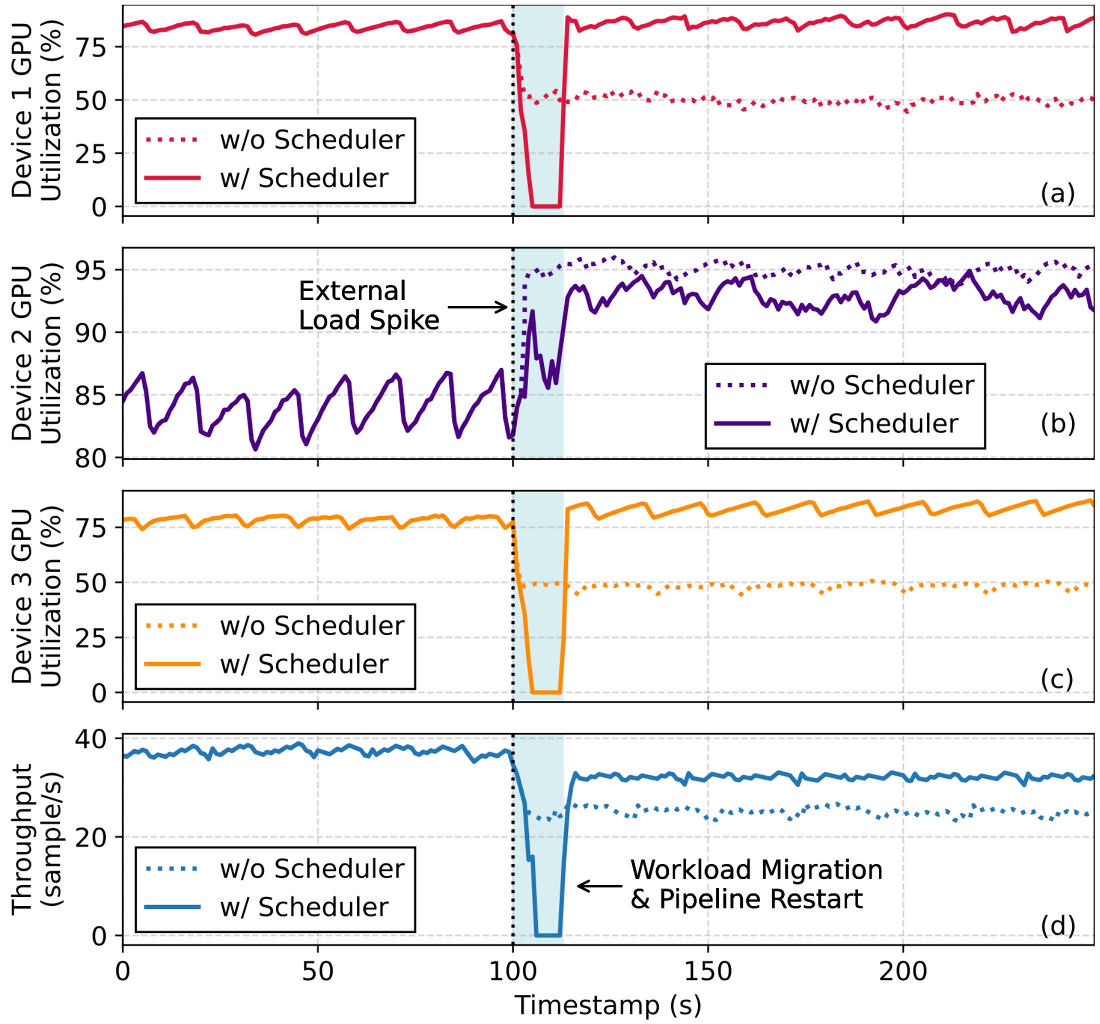
Evaluation

- Pipeline Training Performance
  - Training Results
    - Evaluation on a 2-stage pipeline and a 3-stage pipeline
    - Eco-FL pipeline efficiently collaborates the computation power of all IoT devices and reaches the target accuracy **2.6× faster than data parallelism**.



Evaluation

- Pipeline Training Performance
  - Dynamic pipeline re-scheduling and workload migration
    - An external GPU workload to device 2 at the 100-th timestamp.
    - Without pipeline re-scheduling, the training speed of device 2 will significantly slow down and become lagger in the pipeline
    - With our adaptive pipeline scheduler, device 2 will migrate part of model layers to device 1 and 3 to rebalance the workload across each stage.



Conclusion

- We devise a novel edge collaborative pipeline parallelism to achieve edge resource pooling over trusted devices in proximity for local FL model training acceleration.
- We propose Eco-FL, a hierarchical FL framework upon the edge collaborative pipeline training, which jointly considers both the response latency and data distribution divergence.
- We feature adaptive scheduling in both FL server and client sides to tackle system dynamics inherent in edge scenarios.
- Experimental results show that Eco-FL can upgrade the training accuracy by up to 26.3%, reduce the local training time by up to 61.5%, and improve the local training throughput by up to 2.6× against state-of-the-art baselines.

Thanks!

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