Powering Multi-Task Federated Learning with Competitive GPU Resource Sharing

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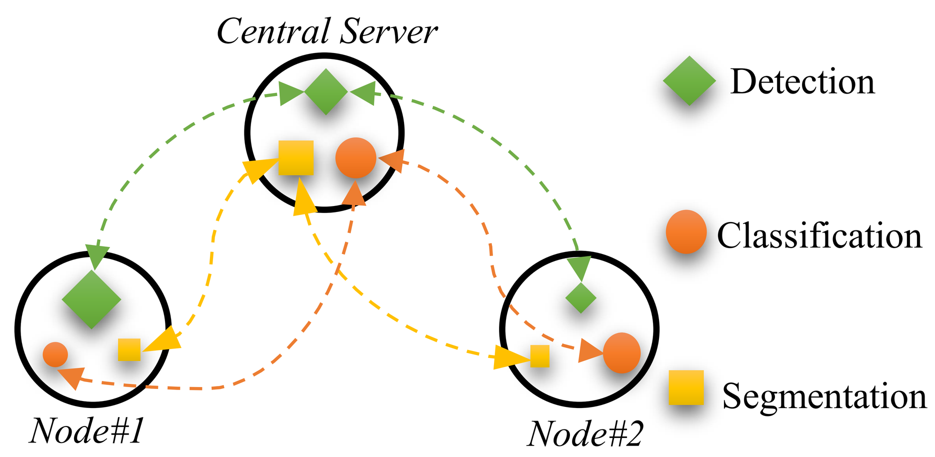
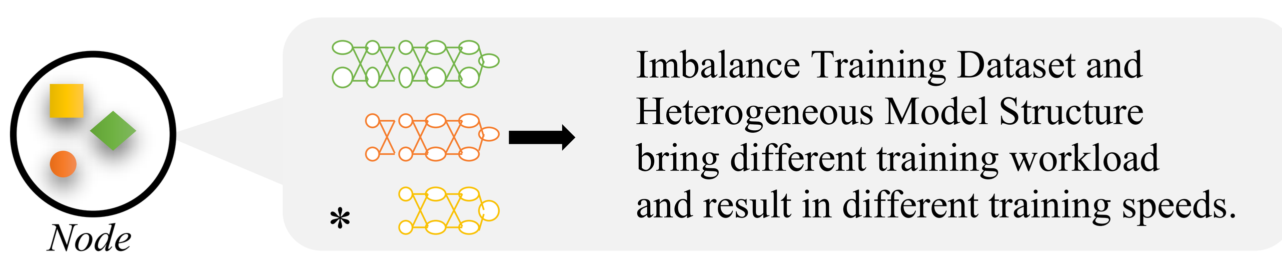
1. Multi-Task Federated Learning

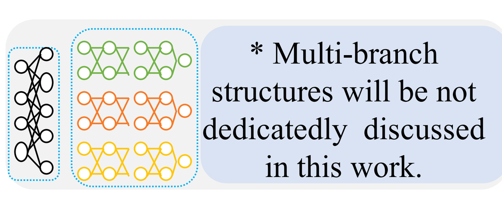
Multi-Task Federated Learning

- Different Learning tasks with
  - Imbalance Datasets
  - Heterogeneous Models
- Learning Speed
  - Multi-Task Synchronization



Multi-Task Deployment with Parallel Model Structures





New Challenges for Computing and Coordination

- Multi-Task Parallel Computing Deployment
- Different Learning Speed Multi-Task Coordination

We propose a full-stack multi-task FL optimization scheme:

- *intra-device GPU scheduling with a competitive resource sharing scheme;*
- *inter- device FL coordination with realistic GPU runtime synchronization.*

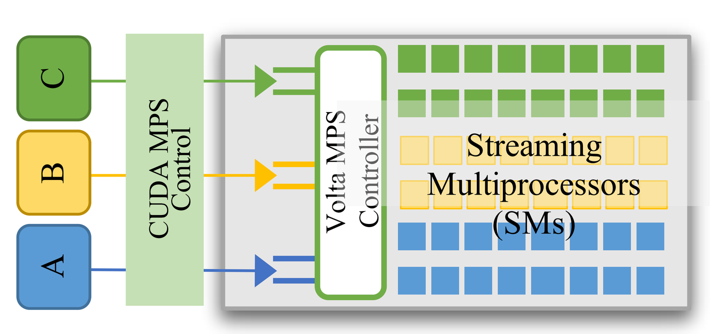
2. Intra-Device Multi-Task Resource Allocation

Multi-Task Parallel Deployment Mechanism

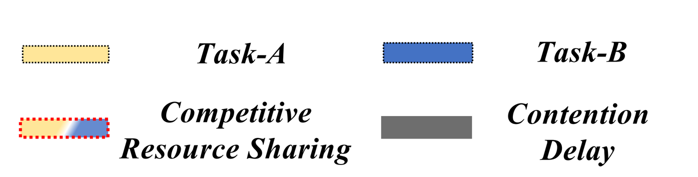
How to achieve effective multi-task dedicated GPU resource allocation.

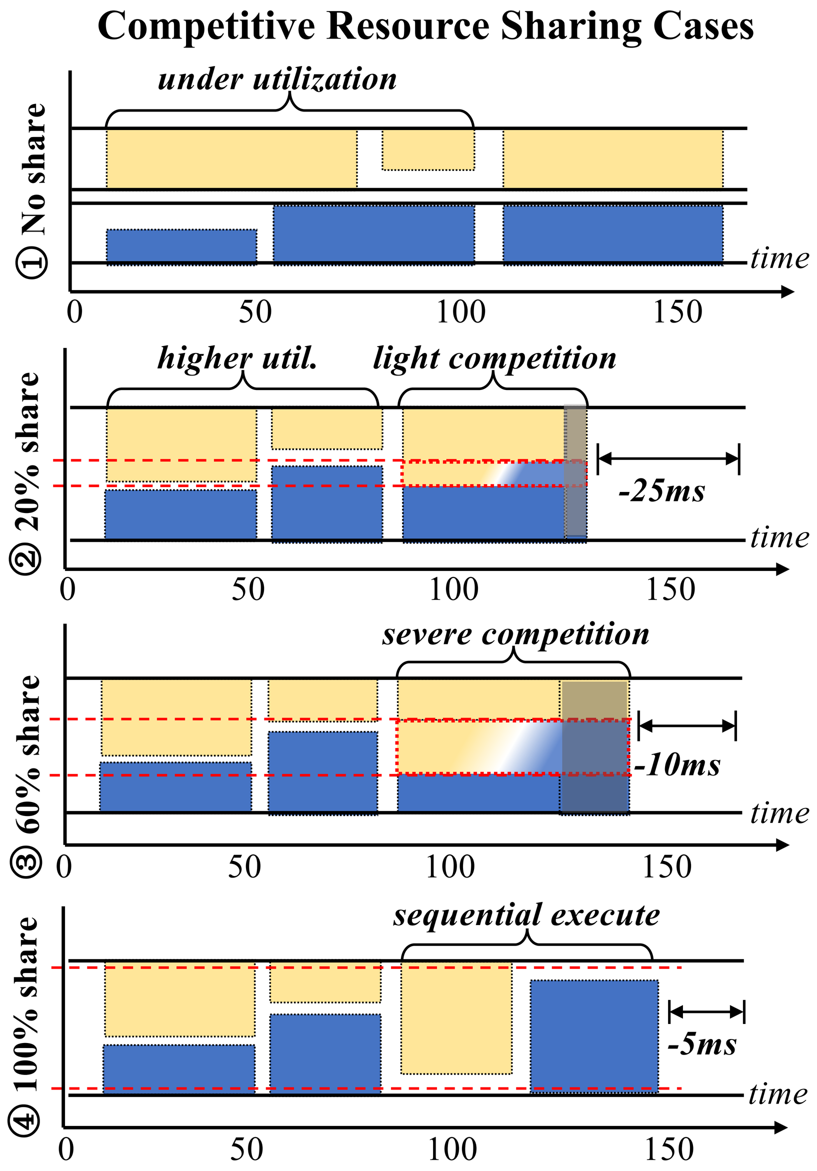
Challenges:

- Identify the parallel computing issue;
- Establish the relationship between
- performance and resource allocation.



Comprehensive Analysis with Competitive Resource Sharing Cases





Isolated Spatial Resource Allocation

Exclusive resource assignment causes under-utilization.

Spatial Sharing with Light Competition

Higher resource allocation flexibility and better resource utilization.

Sharing with Excessive Competition

Leading to resource competition and considerable contention overhead.

Extreme Contention Kills Parallelism

Push back to temporal scheduling when fully sharing the resource without partitioning.

Optimization Insights!

Controlling an appropriate degree of resource competition and sharing is the key to achieve the optimal performance.

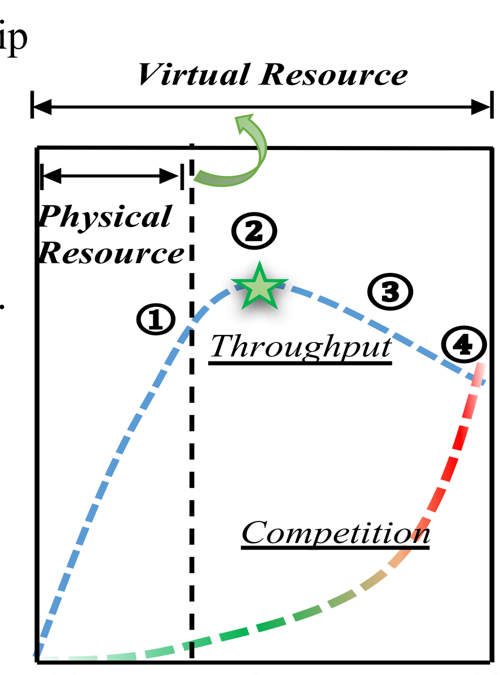
"***Virtual Resource***" management to establish the relationship between performance and resource allocation.

Definition of Virtual Resource *:*

Virtual resource is a number between (*0%~100%*) ×(*I of tasks*).

As shown in the right figure, the four points correspond to the above four cases.

We propose a machine learning approach to estimate the GPU **throughput *P* and achieve the maximum throughput.**



3. Inter-device Multi-Task FL coordination

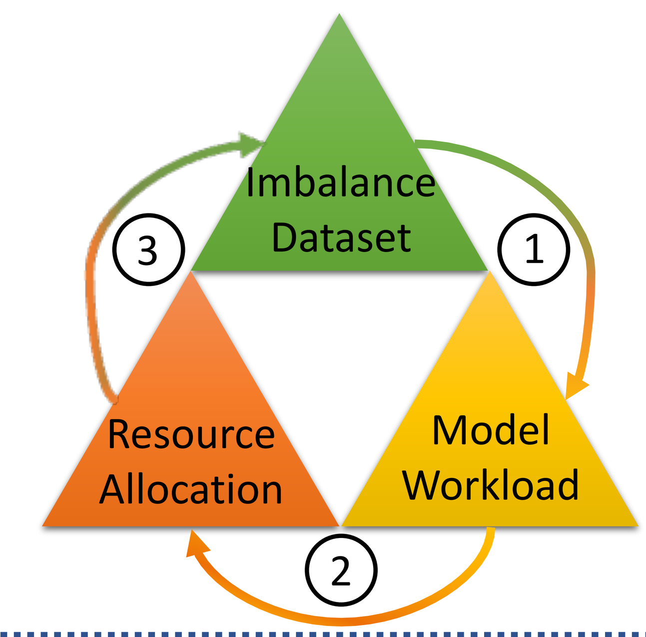
Coordination Design Motivation:

We rethink the FL coordination from a GPU scheduling perspective under imbalance dataset, model workload and resource allocation.

Our Objectives:

(1) Each device could be fully utilized during each synchronization cycle;

(2) Maximize the overall GPU throughput P.



$$\begin{cases} \text{LocalTraining}: \min_{\{W_{0,j}\}_{j=0}} Loss(D_{0,j}, W_{0,j}), \\ Fusing: W_{i,j}^{\{k^{th}cycle\}} = \sum_{j=0}^{J} \frac{|D_{0,j}|}{\sum_{k=0}^{J}|D_{0,k}|} W_{i,j}^{\{k-1^{th}cycle\}}. \end{cases}$$

Multi-Task Federated Learning *with J* devices in a federation cluster, each device has *I* tasks

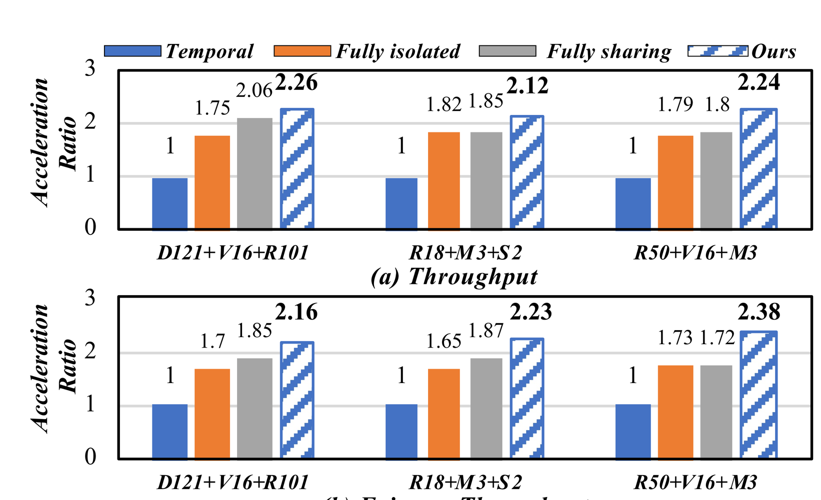
$$\begin{cases} Objective\ 1: \min \sum_i \sum_j \frac{|D_i|}{|D_j|} - \frac{O_i}{O_j}, \\ Objective\ 2: \max \sum_i P_1, \dots, P_i. \end{cases}$$

Tri-party Optimization to Achieve Objective 1:

1. Larger Dataset D need larger Workload O;
2. Larger Workloads O compete for more Resources;
3. More Resources train more data each cycle.

We use greed optimization method to find the optimal batch size and resource allocation.

4. Experimental Results



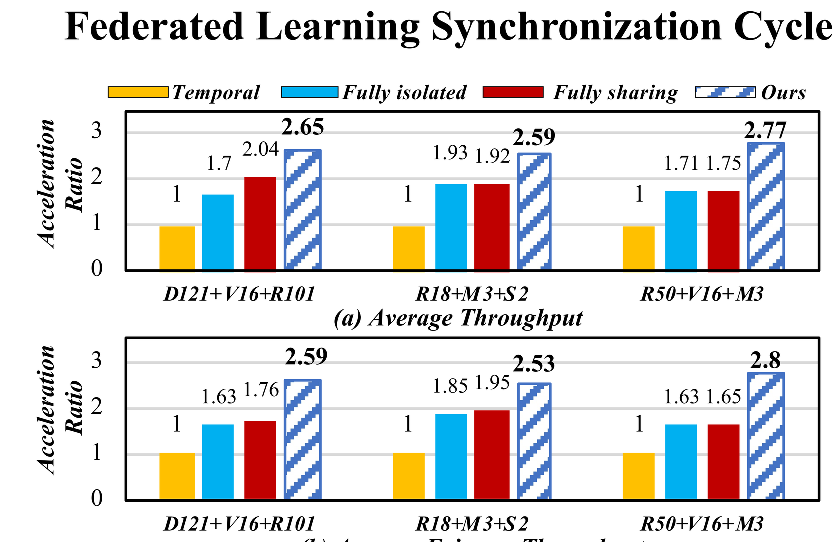
Intra-Device Multi-Task GPU Throughput

We use a FL system with several devices, each devices have three tasks with different model structure and imbalance data volume.

Joint optimization of workload and resource allocation allows our method to utilize GPU resources during the whole synchronization cycle.

We can apply our resources allocation method on various multi-task training scenarios under multiple DNN models' combinations.

Inter-Device Average Throughput in a Federated Learning Synchronization Cycle



5. Contribution and Conclusion

- We analyze the competitive resource sharing mechanism propose an intra-device multi-task dedicated GPU scheduling method.
- We further bring competitive resource sharing mechanism into the inter-device FL cluster and rethink the FL coordination from a GPU scheduling perspective.

Beyond some FL methods which resolve the heterogeneous problems from algorithmic level, FL's heterogeneous research should also dive into computation level due to imbalance dataset, heterogeneous model and different learning speed per task.

6. Reference

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