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FaST-GShare: Enabling Efficient Spatio-Temporal GPU Sharing in Serverless Computing for Deep Learning Inference

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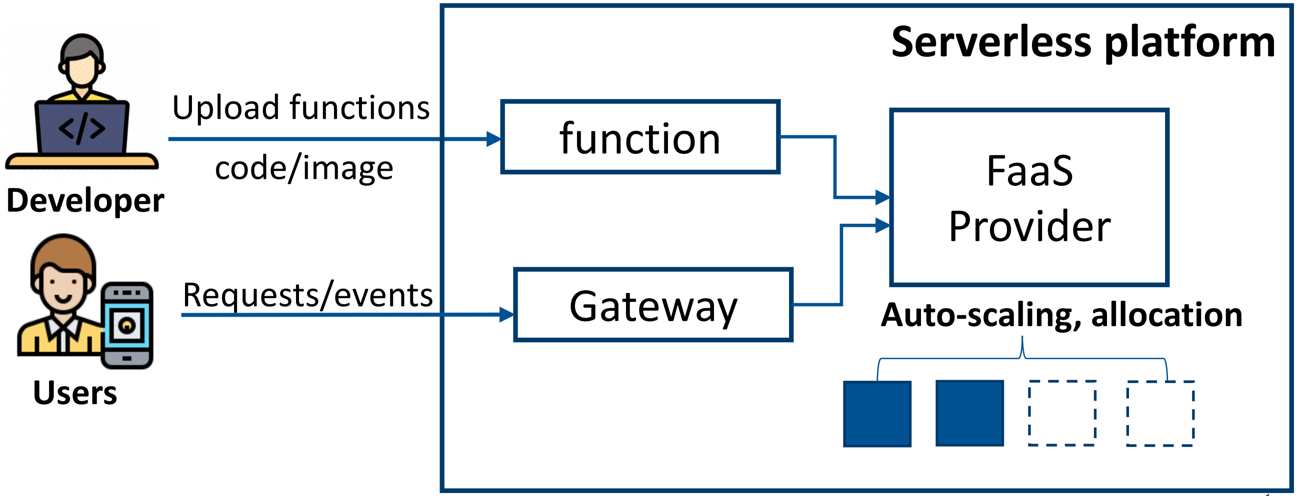
Outline

- Background
- Motivation
- Architecture & Implementation
- Evaluation
- Conclusion

Background – Serverless Computing

- Serverless – Function as a Service (FaaS)
- Advantages
  - Easy deployment;
  - Pay-per-use, Cost-effectiveness
  - Auto-scaling, high scalability;
  - Event-driven, fine-grained.



- Popularity
  - Lambda, Azure Functions, Google Cloud Functions;
  - Problem: only CPU-supported.
  - Serverless DL Inference.
    OSDI22 Orin [10], *ATC22 Jie Li, et. al.* [11],
    VLDB22 Ahsan Ali, et. al. [12].

Only CPU

AWS Lambda

Azure Functions

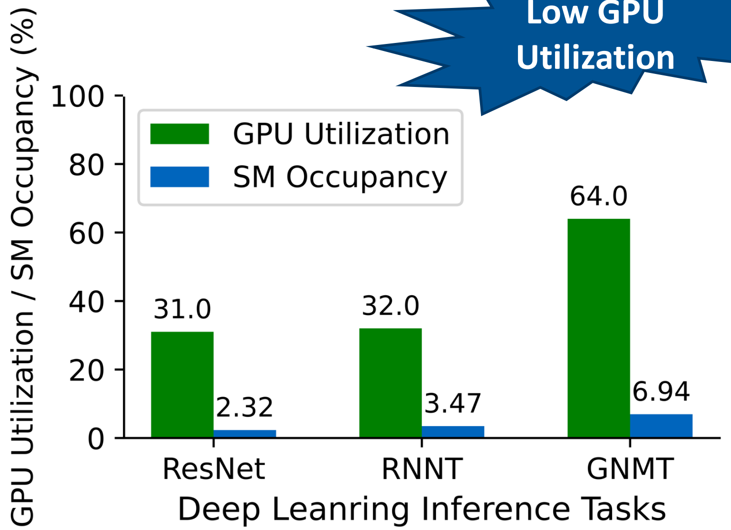
Google Cloud Functions

Motivation – Coarse GPU Usage in Serverless

- GPU Device Plugin for **Kubernetes** [1]
  - Designed for **DL training**, exclusive GPU usage for a container;
  - **GPU under-utilization** in DL inference;

- Time-Slicing GPUs in Kubernetes [2]
  - **Fair time-sharing**, Not guarantee GPU compute power for each pod.
  - Lack of resource **isolation**, Unpredictable interference among FaaS functions.
  - Service Level Objectives (SLOs) violations.

Low GPU Utilization



Kubernetes Device Plugin

NEED!

Both **efficient** and **SLO-aware** GPU sharing mechanism.

Motivation – Fine-grained GPU Sharing

- High GPU utilization == Efficient GPU Usage ?
  - GPU utilization and **SM Occupancy**. (Streaming Multiprocessor)
  - NVIDIA V100 GPU: 80 SM units & A100 HGX GPU: 108 SM units.

- Timing Sharing
  - Previous work: *KubeShare* [38], *Gaia-GPU* [4], *vGPU-scheduler*[5], et. al;
  - **Low SM Occupancy**;

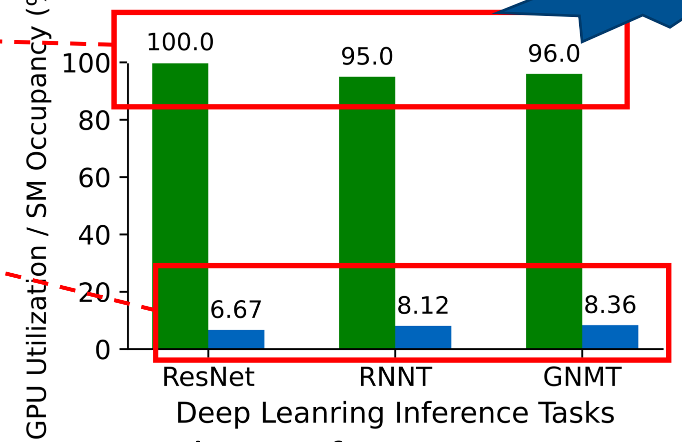
- Spatial Sharing
  - vGPU from **Multi-Instance GPU (MIG);**
    Limited to 7 pre-defined resource configurations;
  - Previous work: *GSLICE* [6], *gpulets* [7], et al.
    Resource-based scaling not compatible with **Instance-based scaling** in FaaS.
  - *Tencent Cloud qGPU* [8] and *Aliyun cGPU* [9]; **Only Spatial Shairng**
    No ***request*** and ***limit*** mechanism**,** not flexible to utilize idle resources.

NVIDIA V100

Low SM Occupancy

GPU Utilization

SM Occupancy



Time sharing from KubeShare[3].

Objectives & Challenges

- Objectives
  - **Spatio-Temporal** GPU Sharing; (Performance Isolation)
  - **SLO-aware**; (Guarantee Function SLOs).
  - **Efficient**; (Throughput, GPU Utilization, and SM Occupancy).

- 4 Challenges
  - How to **coordinate** GPU spatial and temporal multiplexing for performance isolation and efficiency?
  - How to **allocate** the appropriate amount of spatio-temporal resources for each FaaS function?
  - How to **schedule** functions across GPU nodes to ensure its SLO, and improve throughput and GPU occupancy?
  - How to **alleviate** the GPU memory contention with more FaaS functions sharing a GPU?

FaST-GShare

FaaS-oriented Spatio-Temporal GPU Sharing architecture.

Contribution

FaST-GShare

FaST-Manager

- How to **coordinate** GPU spatial and temporal multiplexing to ensure both efficiency and isolation?

FaST-Profiler

- How to **allocate** the appropriate amount of spatio-temporal resources for each FaaS function?

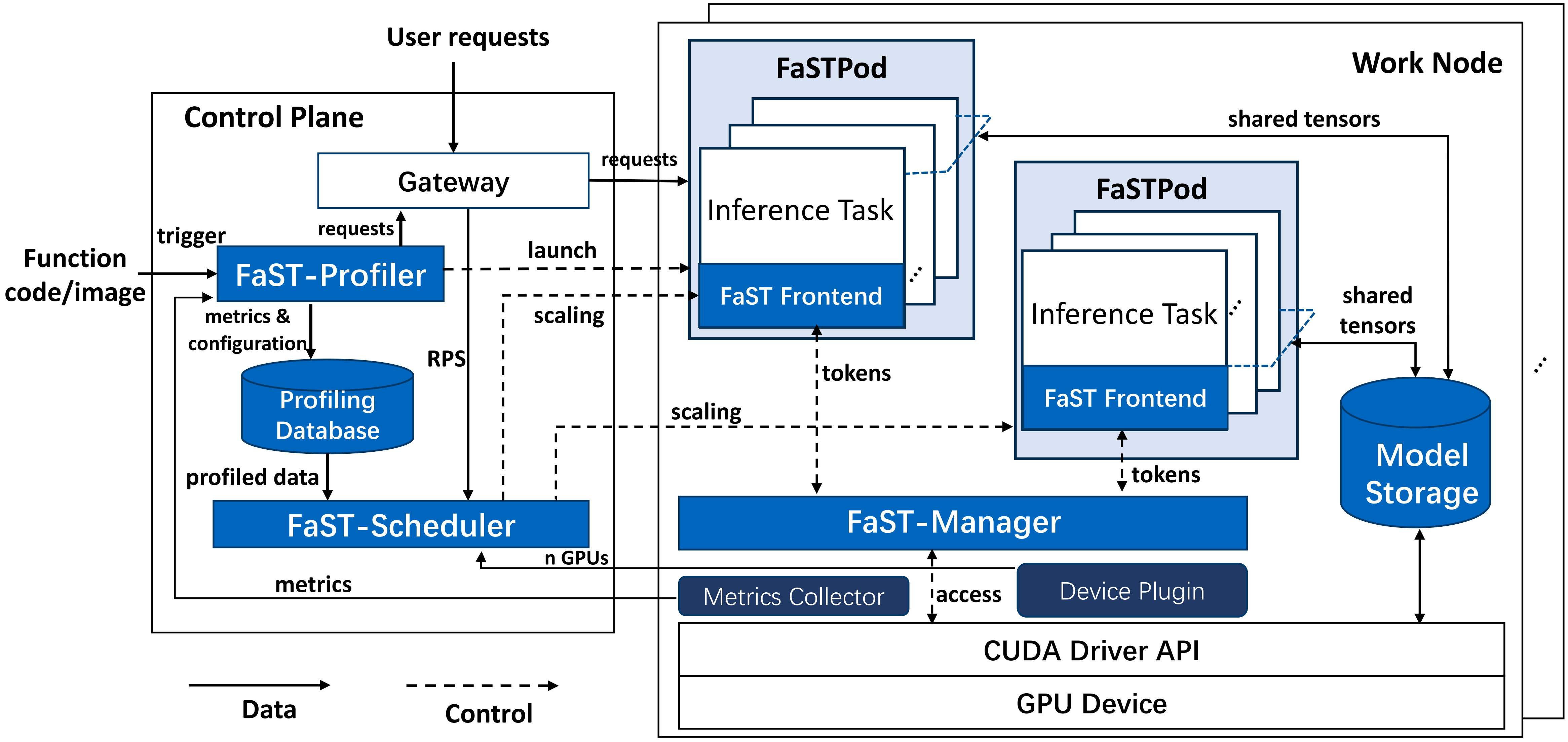
FaST-Scheduler

- How to **schedule** functions across GPU nodes to ensure its SLO and throughput while improving GPU resource usage?

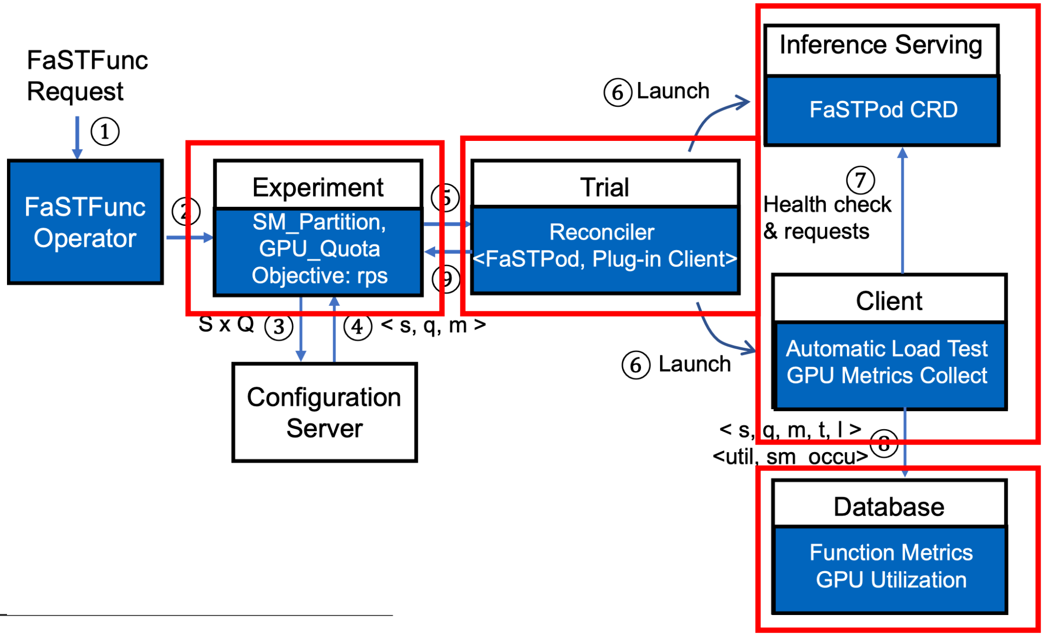
Model Sharing

- How to **alleviate** the increased contension of GPU memory with more FaaS functions sharing a GPU?

Architecture – FaST-GShare Overview



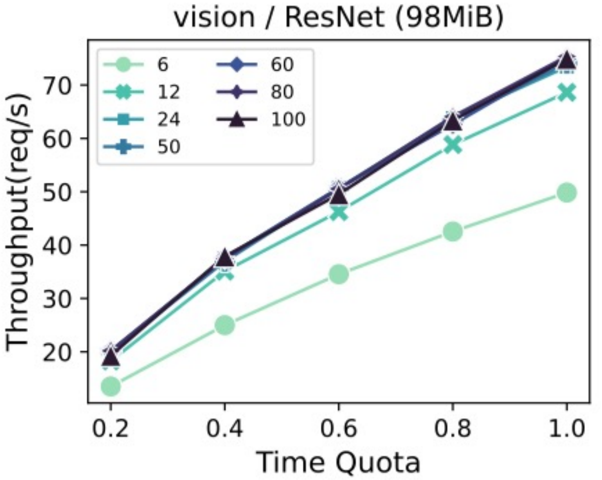
Architecture – FaST-Profiler



- Profiler
  - **Automatic**; **Profile** the function **throughput** under **various spatio-temporal** GPU resource allocations; (Function Performance Curves)
  - **Automatic** Experiment-Trial workflow;

- FaSTPod
  - Basic Deployment Unit;
  - **Any granularity** of spatial and temporal GPU resources.

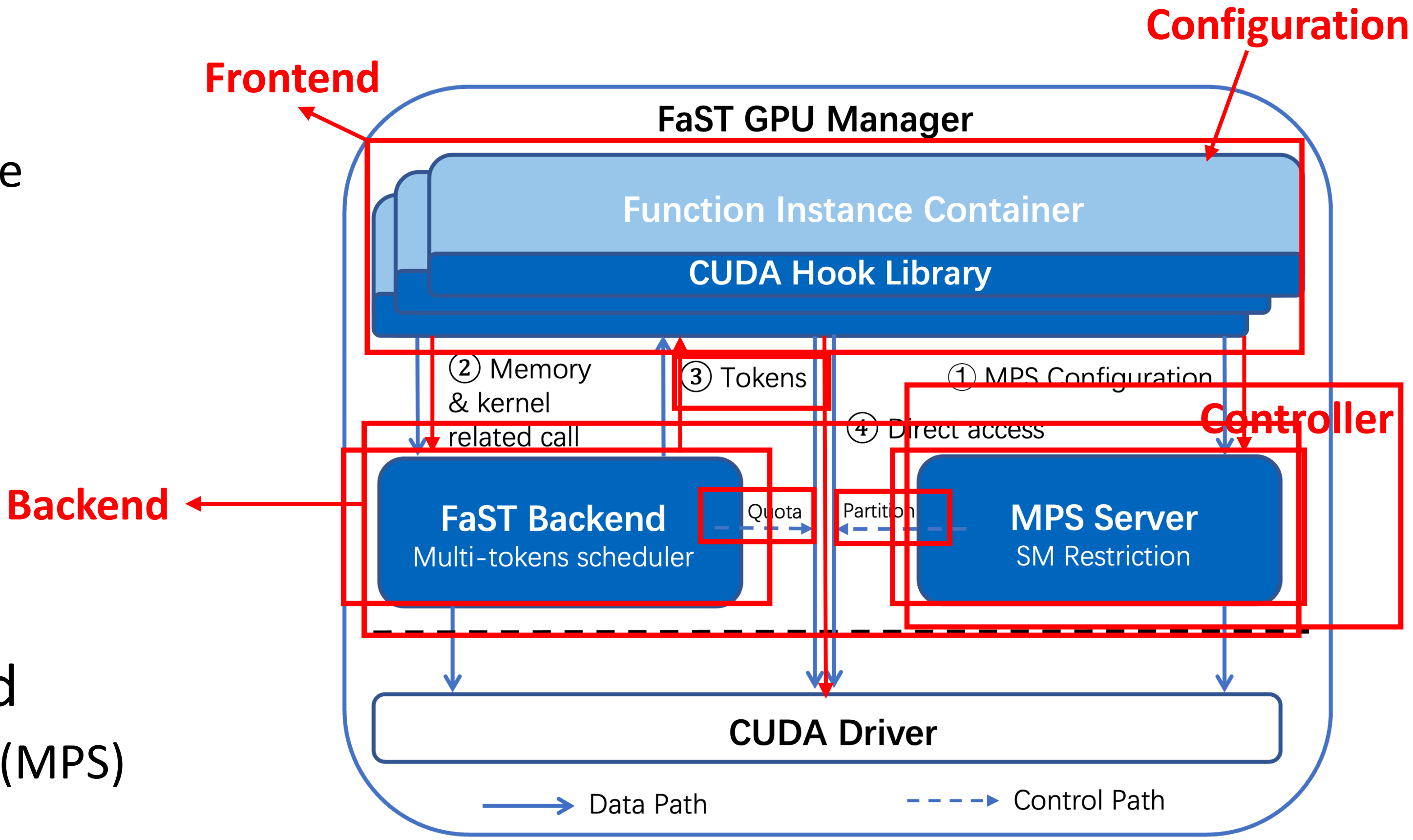
```yaml
apiVersion: faasshare.com/v1
kind: FaSTPod
metadata:
  annotations:
    faasshare/sm_partition: "12"
    faasshare/quota_limit: "0.8"
    faasshare/quota_request: "0.3"
    faasshare/gpu_mem: "1073741824"
  name: fastsvc-rnnt-q30-p12
spec:
  podSpec:
    containers:
    - env:
      - name: MODEL_NAME
        value: MLPerf-FaaS-rnnt
      image: xxxx/mlperf-faas-rnnt:latest
  replicas: 2
```



Function Performance Curves

Architecture – FaST-Manager

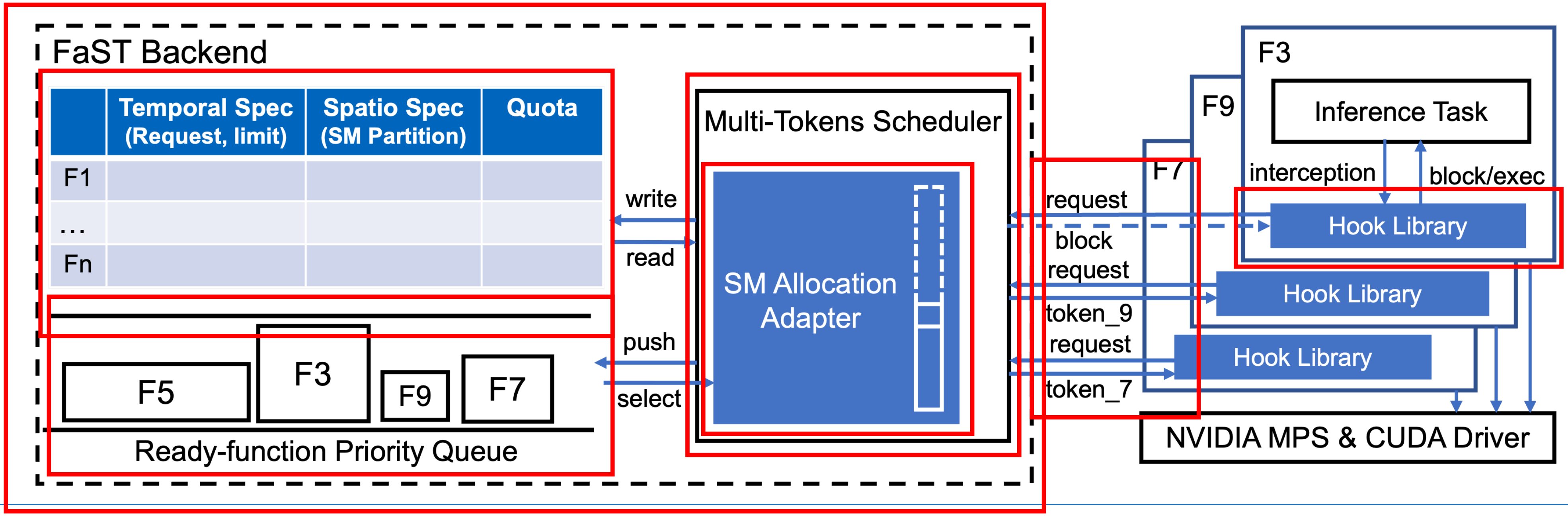
- FaST-Manager
  - **Coordinate** and **Isolate** GPU resource in spatial and temporal dimensions.
  - **Frontend-Backend** mechanism;
  - Tokens: Time slices;



- MPS-based Spatial Sharing Backend
  - Controller for Multi-Process Service (MPS)
  - Exposes the IPC namespace.
  - *CUDA_MPS_ACTIVE_THREAD_PERCENTAGE;*

Architecture – FaST-Manager

- FaST Time Sharing Backend
  - CUDA Driver API **Interception,** Linux *LD_PRELOAD*.
  - Multi-tokens Scheduler;
  - Control Spatial multiplexing through timing tokens → the spatio-temporal limitation collaboration;



Architecture – FaST-Scheduler

- FaST-Scheduler
  - Scale and schedule functions across GPU nodes to guarantee SLOs and improve GPU efficiency.
  - 1. Heuristic Auto-Scaling;
  - 2. Maximal Rectangles Algorithm for node selection;

- Heuristic Auto-Scaling
  - Utilize Profiling data. Decide the number of function pods and corresponding resource allocations;
  - Scaling-up and Scaling-down;
  - A metric RPR;
  - Priority queue in the ascending order by RPR.

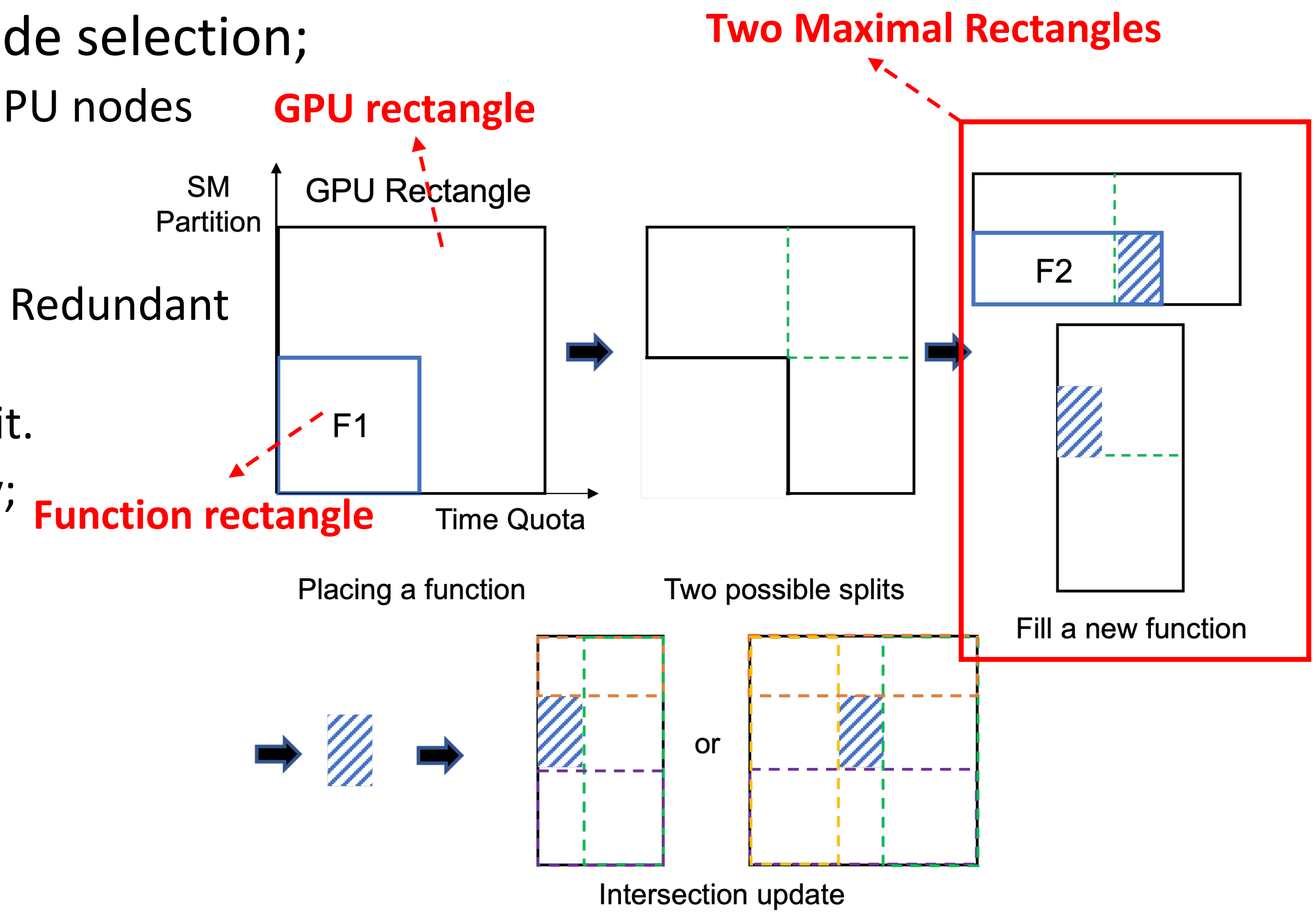
Processing gap

$$\boxed{\Delta RPS_j} = R_j - \left(\sum_{J_i \in F_j} T_{j,i}\right)$$

$$\boxed{RPR \text{ (RPS per Resource)}} = \frac{T_{j,p}}{S_{j,p} * Q_{j,p}}$$

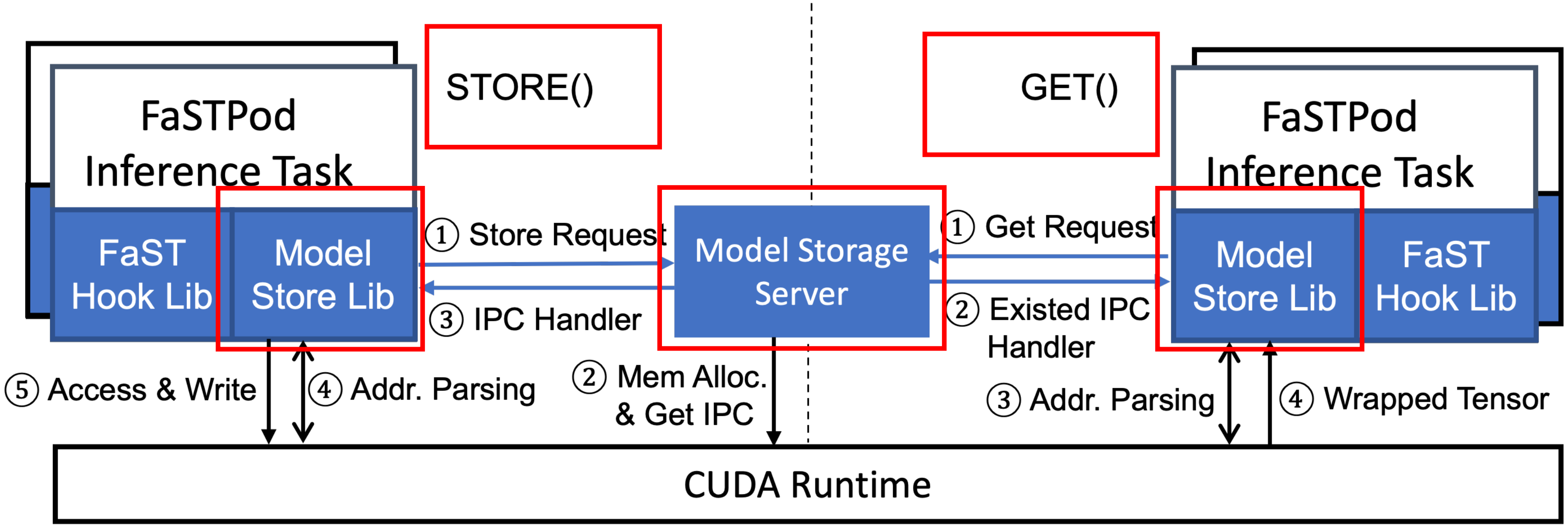
Architecture – FaST-Scheduler

- Maximal Rectangles Algorithm for node selection;
  - Effectively schedule function pods to GPU nodes
  - Dynamic 2D resource **restructuring**.
  - **GPU rectangle** and **function rectangle**.
  - 3 Steps: Split, Intersection update, and Redundant rectangle removing;
  - Two maximal rectangles during the split.
  - Reclamation: "keep-restructure" policy;



Architecture – Model Sharing

- Model Sharing Storage
  - Mitigate memory contention.
  - Model Store Library and Model Storage Server.
  - STORE() and GET().



Experiment Setup

- Testbed
  - Serverless platform: **OpenFaaS** with **faas-netes**.
  - The master node: Intel(R) Xeon(R) CPU @ 2.00GHz with 48 cores and 60GB RAM.
  - **4 work nodes**, each with a **NVIDIA Tesla V100 GPU** with 80 SM units, and **16GB device memory**.

- Workload
  - **MLPerf Benchmark** [14] from NVIDIA, including **ResNet**, **BERT**, **RNNT**, and **GNMT**;
  - Larger transformer models: **ResNeXt** [37] (vision) and **ViT_huge**[16];
  - ML framework: **PyTorch** and **TensorFlow**;

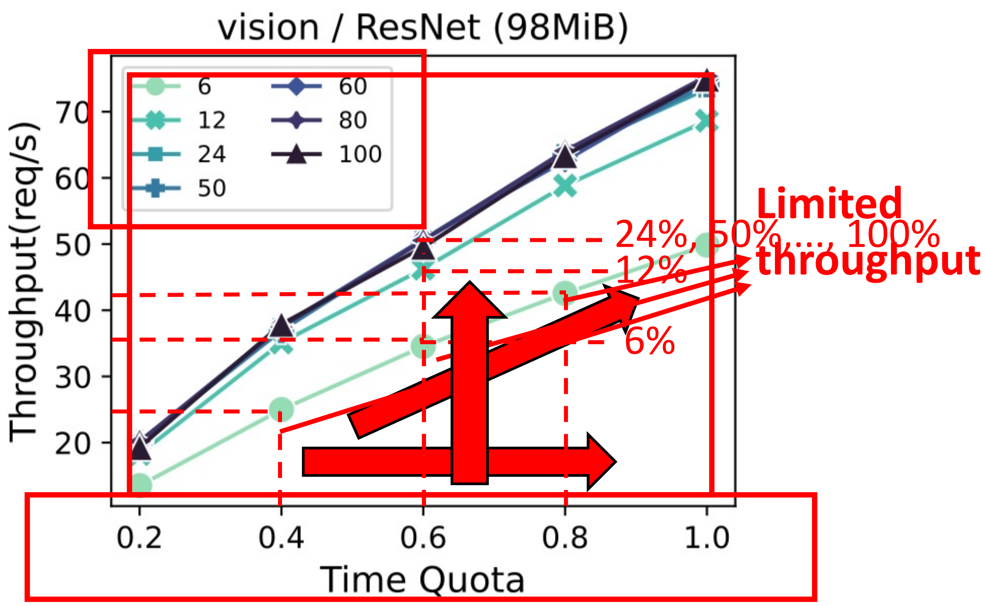
Evaluation – Performance Isolation

- Profiling points
  - Temporal dimension: 0.2, 0.4, 0.6, 0.8, 1.0.
  - Spatial dimension: 6%, 12%, 24%, 50%, 60%, 80%, 100%;

- Temporal dimension
  - The throughput of the model increases proportionally.
  - **Limited throughput →** **Effective temporal resource isolation.**

- Spatial dimension
  - At a certain point, the throughput will no longer increase.
  - → **A model cannot fully occupy all SMs**;
  - → **Effective spatial resource isolation;**

- → Profiling performance curves for FaST-Scheduler



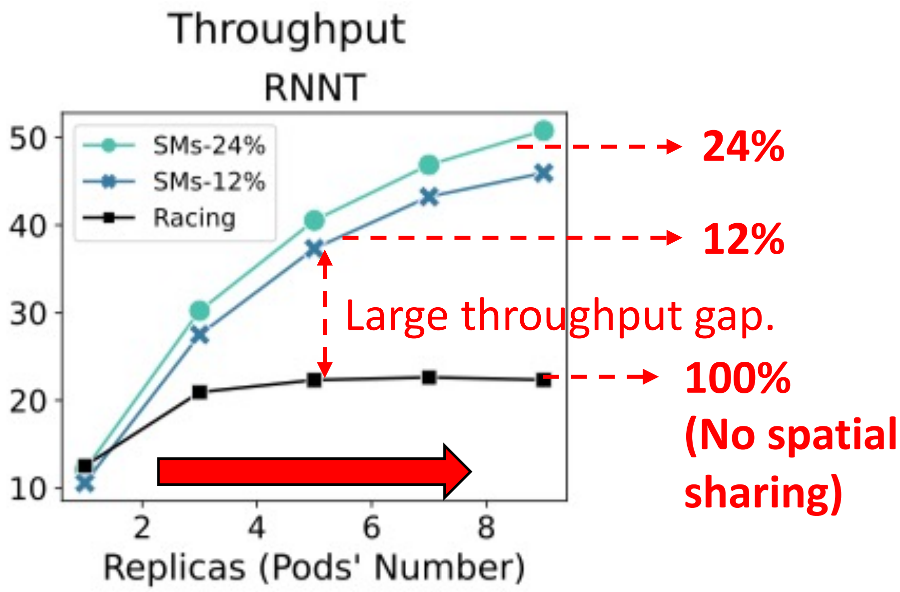
Function throughput of ResNet from FaST-Profiler.

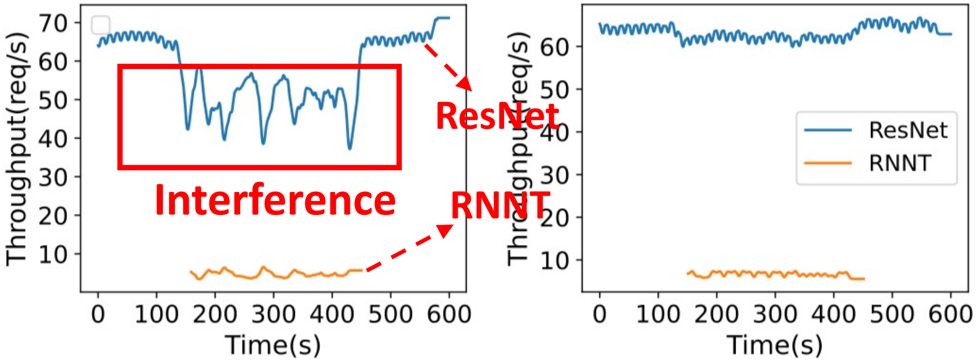
Evaluation – Spatial Sharing Performance

- 100% time quota allocation
  - No spatial sharing (racing, 100% partition).
  - 12% partition;
  - 24% partition;

- **Throughput Improvement:**
  - **Improve throughput by x3.15.**

- **Avoid Interference**
  - Time quotas (limit):
ResNet: 80%, RNNT: 50%.   >100%
  - **Effectiveness of spatial sharing in FaST-Manger.**



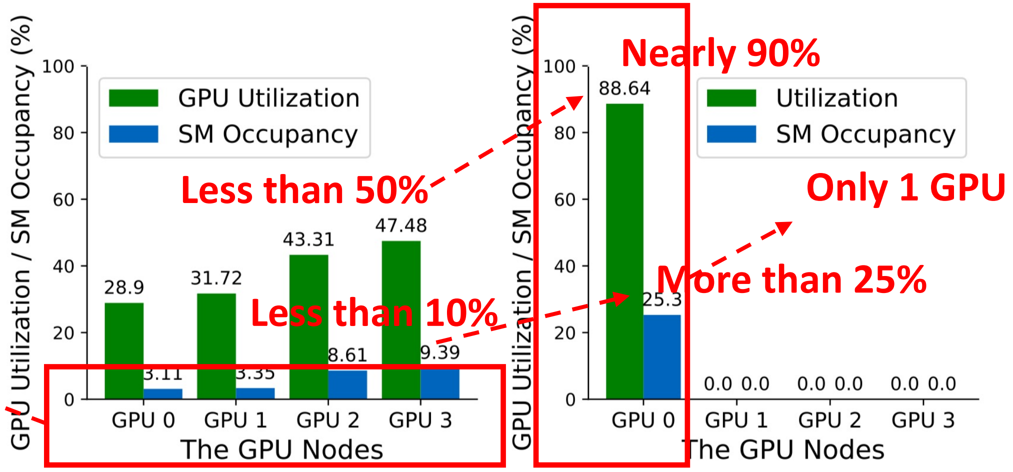


(a) Only time sharing. **(b) Spatio-Temporal sharing.**

Evaluation – Efficient FaST-Scheduler

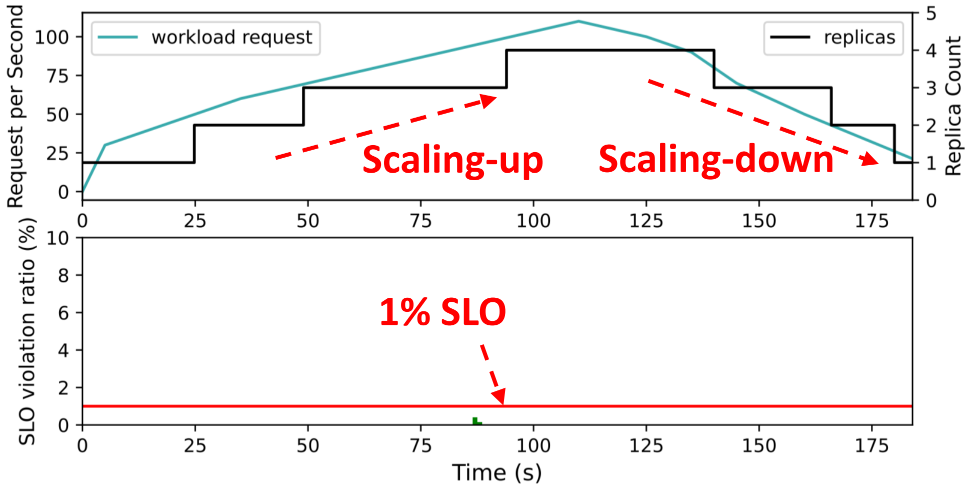
- Workload (SM partitions, time quotas)
  - 4 ResNet pods, (12%, 40%)
  - 2 RNNT pods, (24%, 40%)
  - 2 BERT pods, (50%, 60%)

4 GPUs



(a) Only time sharing [38]. (b) FaST-Scheduler.

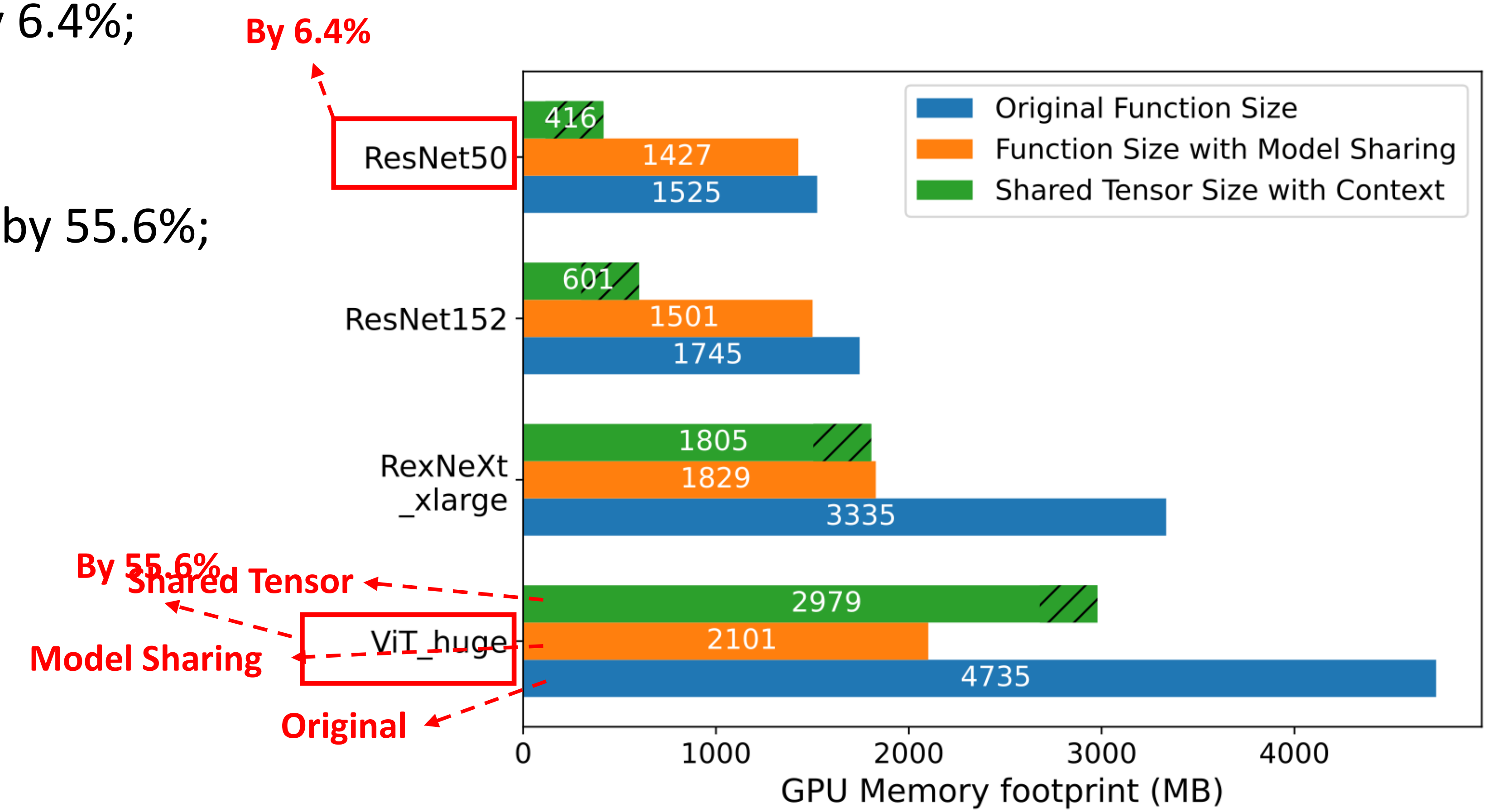
- **GPU utilization and SM occupancy Improvement**
  - **4 GPUs → 1 GPU**
  - **GPU utilization by x1.34,**
    SM occupancy by x3.13 on average;



- **SLO-Aware**
  - Effective Auto-scaling;
  - ResNet SLO of 69ms, **no SLO violation** exceeding 1% .

Evaluation – Model Sharing

- ResNet model decreased by 6.4%;
  - 1525M to 1427M
- ViT_huge model decreased by 55.6%;
  - 4735M --> 2101M



Conclusion

- **FaST-GShare**
  - An efficient FaaS-oriented Spatio-Temporal GPU Sharing architecture for deep learning inferences;
- **FaST-Manager**
  - Limit and isolate spatio-temporal resources for GPU multiplexing.
- **FaST-Profiler** & **FaST-Scheduler,**
  - Guarantee function SLOs and maximize GPU usage;
- **Model Sharing**
  - Alleviate Memory Contention;
- **Performance**
  - Improve throughput by 3.15x, GPU utilization by 1.34x, and SM occupancy by 3.13x on average.