FluidFaaS: A Dynamic Pipelined Solution for Serverless Computing with Strong Isolation-based GPU Sharing

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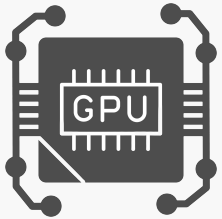
01 Introduction and Problem Overview

Introduction

Growing Interest in ML Inference on Serverless Platforms with GPU support:

- Ease of programming, maintenance, autoscaling, and pay-as-you-go billing



GPU Sharing with MPS and MIG:

MPS (Multi-Process Service):

- Suffers from weak isolation (share GPU's memory and compute resources)
- Causes performance interference and security concerns

MIG (Multi-Instance GPU):

- Provides strong isolation (separate compute, memory, data paths)
- No performance interference from other process

- To overcome these issues with MPS, recent research and industry (e.g., Kubernetes) have shifted focus to MIG (Multi-Instance GPU), which offers strong isolation by hardware partitioning.

Problem Statement

LImitations of Previous Research/MIG:

- Fragmented GPU Resources
    a. MIG slices across GPUs are often small and scattered
    b. No single MIG slice may be large enough when needed → function has to wait.

- Rigid MIG Reconfiguration
    a. Changing MIG layout takes several minutes
    b. Incompatible with the dynamic and bursty nature of serverless workloads

- Monolithic Function Design
    a. Prior systems (e.g., ESG) require: Entire function must fit on one MIG slice
    b. This leads to: Wasted resources, Long delays, Poor scalability

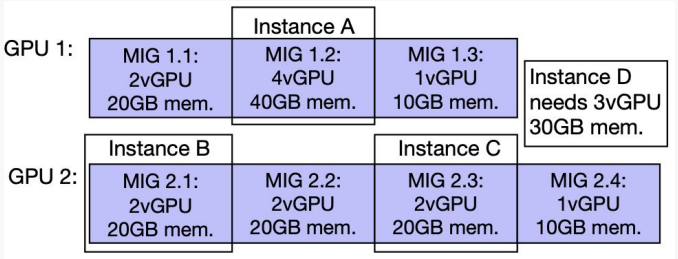


Figure : Current MIG support in serverless computing cannot make serverless function "instance D" utilize idle resources fragmented into multiple MIGs.

02 Background and Related Work

Serverless Platform

Serverless Platform

- **Platforms:** OpenWhisk, Knative, OpenLambda, OpenFaaS
- **Controller:** Scales functions up/down based on load
- **Load Balancer:** Routes requests to available invoker nodes
- **Invoker:** Runs function instances; manages job queues

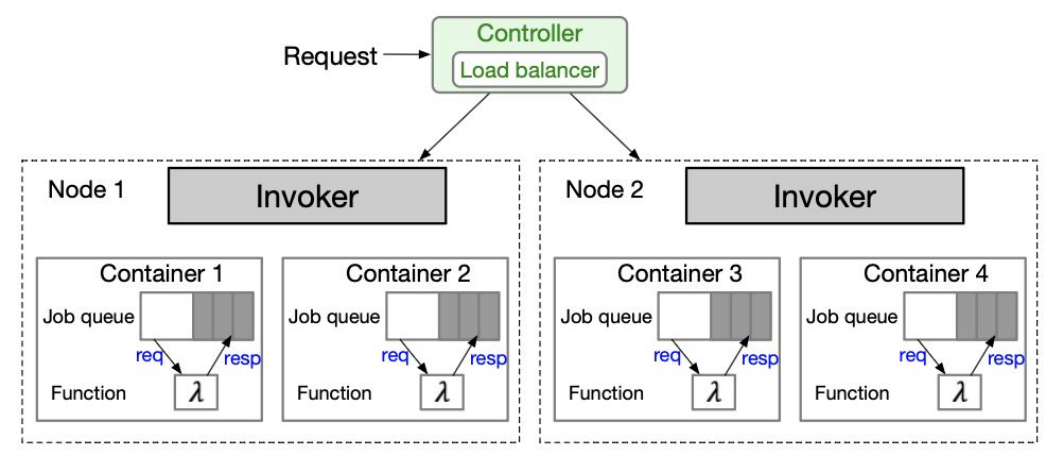


Figure: Overview of existing serverless platforms.

Related Work – Why Existing Solutions Fall Short

INFless, Protean, Llama:

- Use MPS for GPU sharing
- Suffer from interference due to weak isolation

FaaSwap

- Uses model swapping to time-share GPUs
- Incurs warm-start delays and reloading overhead

ESG, Miso:

- Use MIG for stronger isolation
- Treat functions as monolithic units
- Can’t combine idle fragmented slices (e.g., 1g.10gb + 2g.20gb)

StreamBox, Orion:

- Stream-level or application-level GPU sharing
- Optimized for DAG-based inference workflow composed of fine-grained functions
- No isolation

03 Motivation Analysis

Underutilization of GPU Resources in MIG-based Serverless

Setup:

- Workloads: DNN inference pipelines from Azure Functions trace
- Platform: ESG (MIG-enabled serverless scheduler)
- Hardware: A100 GPU with 3 MIG slices – 4g.40gb, 2g.20gb, 1g.10gb

Key Observation:

- ESG considers a GPU "utilized" if any one MIG is active
- At peak load (83s), ESG's resource demand exceeds ideal by 167%

Root Cause:

- Fragmented small slices (e.g., 1g, 2g) remain idle
- ESG's static, monolithic scheduling can't utilize them

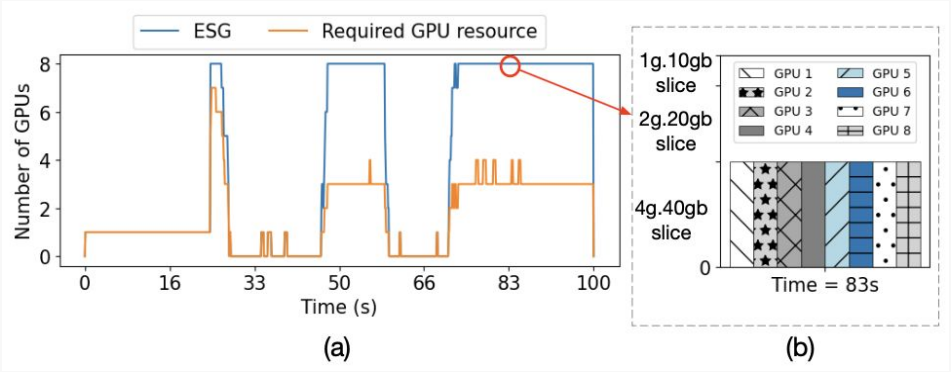


Figure: (a) GPU utilization in ESG and the required GPU resources. For ESG, a GPU is considered utilized if it is processing requests. (b) MIG usage at the 83rd second.

Problem: Fragmentation

Resource Fragmentation:

- MIG slices can't be flexibly recombined at runtime
- Even if aggregate capacity is enough, function fails if no single slice matches
- Example: 2g.20gb + 1g.10gb idle, but request needs 3g.40gb → must wait

Illustrated in Figure:

- GPUs with idle slices can’t serve new requests
- Forces unnecessary allocation of additional GPUs

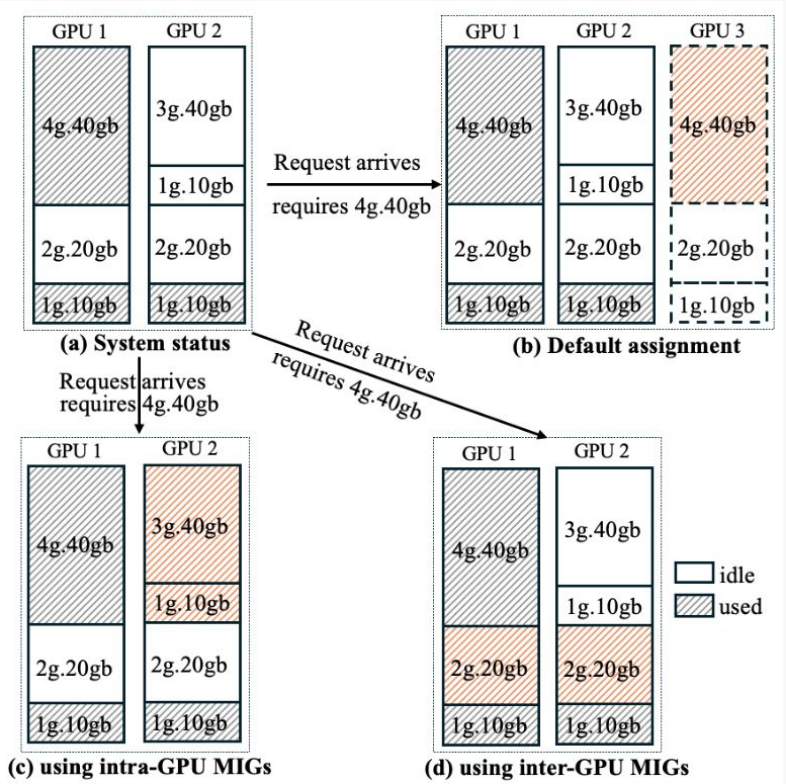


Figure: Illustration of GPU resource fragmentation

Problem: Exclusive Keep-Alive

Exclusive Keep-Alive Policy

- Once a model is loaded, its MIG slice is locked — even when idle
- Prevents sharing and reuse by other functions

Empirical Finding:

- Avg. active MIG usage = 16.1%
- For 90% of time, MIGs used <35% of their capacity

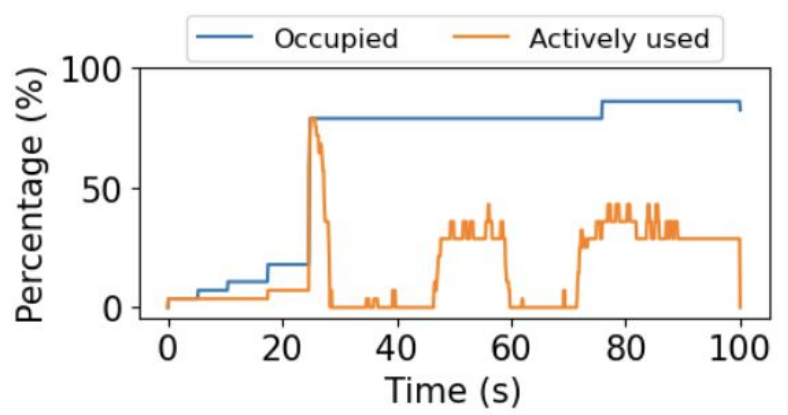


Figure: The occupied and actively used GPU percentage

Proposed Solution and Key Challenges

Solution:

- FluidFaaS dynamically splits a serverless function into pipeline stages, each assigned to a fragmented MIG slice.
- This enables fine-grained GPU utilization without requiring costly MIG reconfiguration.

Challenges:

1. **Lack of Dynamic Pipeline Support**
    - Existing serverless platforms require static function containers.
    - No native support for runtime DAG construction and resource-aware execution.
2. **Cross-MIG Communication Overhead**
    - MIG slices are hardware-isolated.
    - Communication between stages must go through CPU memory, adding latency.
3. **Complexity in Scheduling & Scaling**
    - Functions may run in multiple forms (pipeline vs. full).
    - Scheduling must handle eviction, instance heterogeneity, and meet SLOs.

04 Design of FluidFaaS

FluidFaaS Overview

Break a serverless function into smaller stages and run them on fragmented MIG slices as a dynamic pipeline

- Splits functions into DAG-based pipeline stages
- Maps each stage to available fragmented MIG slices
- Dynamically constructs and schedules GPU pipelines at runtime
- Addresses MIG fragmentation and rigidity in GPU resource allocation

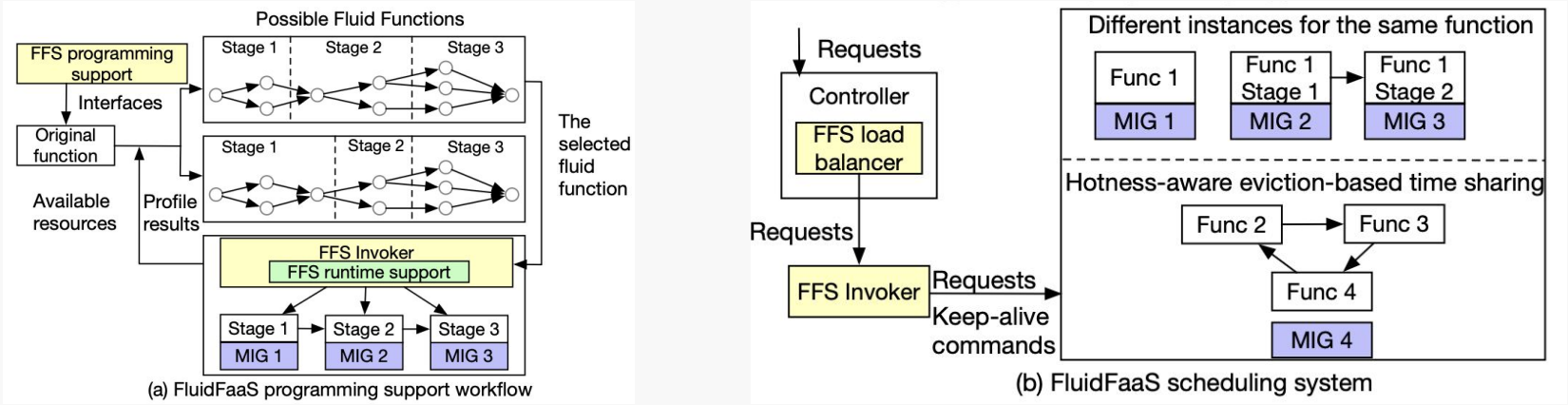


Figure 6: Overview of FluidFaaS.

Automatic Pipeline Instance Construction

A. Programming Support

- Breaks monolithic functions into components using a DAG.
- Each node in the DAG is profiled for memory and execution time on MIG slices.
- Invoker assigns available MIGs to nodes at runtime and stores this config.

a. Programming Interface

- Use **FluidFaaS.Module** instead of **nn.Module**.
- Register components with **.reg()** to build the DAG.
- Use **FFaaS** to manage DAG creation and execution.
- Modes:
  - **BUILDDAG**: Build DAG and profile DAG offline.
  - **RUN**: Load DAG and execute with MIG mapping.

```
import FluidFaaS as FFS

class model1(FFS.Module):
  ... # define DNN model1 as defining a Torch DNN model

... # definition of other DNN models

class MyFFaaS (FFS.FFaaS):
  def __init__ (self, event, context):
    super().__init__(self, event, context, mode)

    ... # other initialization operations as needed

  def defDAG(self, x, y):   # define self.dag
    x1 = model1.reg(self, x)
    x2 = model2.reg(self, x)
    x3 = model3.reg(self, x1,x2)
    x4 = model4.reg(self, x3)
    x5 = model5.reg(self, x4, y)

# entry point of a Serverless Function in normal execution
def MyHandler_run (event, context):
    fluidFaaS = MyFFaaS (event, context, RUN)
    fluidFaaS.run()
    ...

# entry point of a Serverless Function for DAG construction
def MyHandler_buildDAG (event, context, BUILDDAG):
    fluidFaaS = MyFFaaS (event, context, BUILDDAG)
    profiles = MyFFaaS.profile()
    ...
```

Figure: Illustration of the programming of a FFaaS function.

Automatic Pipeline Instance Construction

b. Runtime Support of FFaaS

- Loads DAG and MIG assignments in RUN mode.
- Spawns one process per stage on assigned MIG slices.
- Uses shared CPU memory to pass data between stages.
- Manages execution and termination with minimal developer code.

```
class FFaaS:
    def __init__(self, event, context, mode):
      if (mode == 'RUN'):
         self.dag = self.importDAG()
         self.migs = self.importMIGs()
         self.stages = self.importStages()
         self.eviction = [False] * len(self.migs)
      elif (mode == 'BUILDDAG'):
         ...
    def _load_models(self, DAG):
        #load models for all stages
    def _run_inference(self, stage, queue, next_queue, shared_data
     , nextShdata):
        device = torch.device("cuda")
        while True:
            input = self._get_from_shared_memory(shared_data).to(
     device)
            if input not empty:
                # Run all components in stage based on the DAG
                output = model(input)
                self._write_to_shared_memory(nextShdata, output)
                next_queue.put()
            # Placeholder for actual eviction condition
            if self.eviction[stage]:
                model.cpu()
                del model
```

```
def _get_from_shared_memory(self, shared_data):
   #get data from shared memory
def _write_to_shared_memory(self, shared_data, data):
   #write data back to shared memory
def _start_processes(self):
    #start a process for each stage in one mig
    for i in range(len(self.stages)):
        os.environ["CUDA_VISIBLE_DEVICES"] = self.migs[i]
        torch.cuda.init()
        p = mp.Process(
            target=self._run_inference,
            args=(self.stages[i], self.queues[i], self.queues[
 i+1], self.shared_data[i], self.shared_data[i+1])
        )
        self.processes.append(p)
        p.start()
def _terminate_processes(self):
   #terminate processes when eviction happens
   #By modify self.eviction to True
def profile(self):
   ...
def _initialize_shared_memory_and_queues(self):
   #initialize shared memory and job queues
def run(self):
    self._initialize_shared_memory_and_queues()
    self._load_models()
    self._start_processes()
    self._terminate_processes()
    # Cleanup shared memory
```

Each stage runs as an independent process, passing data via shared memory like steps in a pipeline — all managed by FFaaS internally.

Figure: Implementation of the core runtime support FFaaS

Automatic Pipeline Instance Construction

B. Runtime Support in Invoker

Goal: Dynamically construct and schedule balanced pipelines using available MIG slices.

Invoker as Local Scheduler:

- Runs on each GPU node independently
- Constructs pipelines based on real-time resource availability and offline profile data
- Assigns MIG slices to DAG components
- Operates without relying on the central controller

Pipeline Construction Strategy:

- All pipeline partitions are pre-evaluated offline for various combinations of resources
- Applies Coefficient of Variation (CV) for balance: *CV = std(t1,...,tn)/mean(t1,...,tn)*
- At runtime, selects the most balanced, MIG-fit pipeline

[DAG + Profile] + [Available MIGs] → [Select best-fit pipeline] → [Write Config for each Slices]

Hotness-aware Eviction-based Time Sharing

Problem: GPU slices remain underutilized due to fixed warm bindings.

Solution: Dynamically evict low-usage instances to share MIGs.

Multi-level Keep-Alive States:

Exclusive Hot:

- High-load instances stay fully loaded on MIG.
- Not evicted; ensures fast access and SLO compliance.
- All pipeline stages are in this state.

Time Sharing:

- Low-utilization (<30%) instances.
- Stored in CPU memory if idle (warm)
- Can be evicted and reloaded as needed.
- Terminated if inactive (cold).

Eviction Policy:

- Evict least recently used (LRU) time-sharing instance if MIG is needed.
- Reload instance from warm state (CPU) if accessed again.

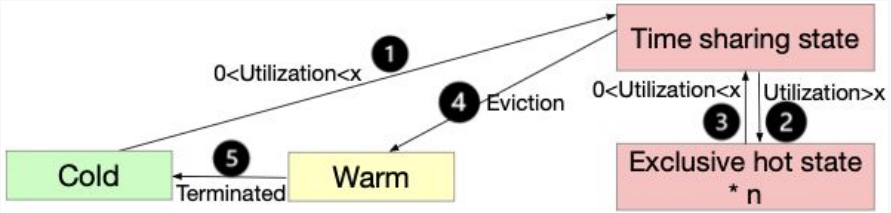


Figure: The state transition details.

05 Evaluation & Results

Evaluation Methodology

Baseline:

- **ESG:** State-of-the-art MIG-aware scheduler
- **INFless:** Strong MPS-based GPU sharing for inference (added MIG support)

Testbed Setup:

- 2 nodes, each with:
  - 8 × NVIDIA A100 80GB GPUs
  - 4 × AMD EPYC 7763 CPUs, 1440 GB RAM
- MIG Partition (default): 4g.40gb, 2g.20gb, 1g.10gb per GPU

Workload Traces:

- Real Azure Functions invocation traces
- Each app tested in 3 sizes: small, medium, large

Applications (from ESG)

- App 0: Image classification
- App 1: Depth recognition
- App 2: Background elimination
- App 3: Expanded image classification (DAG with branching)

SLO Configuration:

- **SLO Scale =** 1.5× the runtime of isolated execution
- Measures whether inference finishes within latency targets

End-to-End Performance

SLO Hit Rate:

- FluidFaaS consistently outperforms both baselines in medium and heavy workloads:
  - Up to 90% improvement in SLO hit rate (vs. INFless)
  - Similar performance to ESG in light workloads

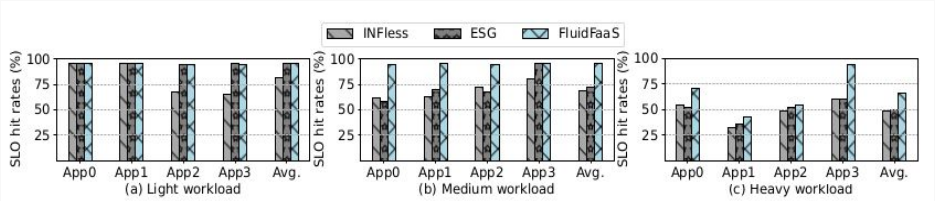


Figure: SLO hit rate in different workloads for each application

GPU Time & MIG Time:

- FluidFaaS uses less GPU time than INFless across all workloads:
  - Up to 17% reduction (vs. INFless in heavy workload)
  - Up to 6% reduction compared to ESG
- MIG time is similar across all systems
  - Max difference: ≤7%
  - Confirms FluidFaaS maintains efficiency without increasing slice usage

Workload		Light workload			Medium workload			Heavy workload		
Method		INF	ESG	Fluid	INF	ESG	Fluid	INF	ESG	Fluid
Norm.	MIG time	0.95	0.96	1	0.93	0.99	1	0.94	0.97	1
	GPU time	1.08	1.07	1	1.06	1.05	1	1.17	0.99	1

Table: Resource cost comparison, where the result of Fluid-FaaS is normalized to 1. The lower, the better. INF is INFless and Fluid is FluidFaas.

End-to-End Performance

Throughput

- FluidFaaS improves throughput by:
  - +75% in heavy workloads
  - +25% in medium workloads
  - Similar performance as ESG in light workloads

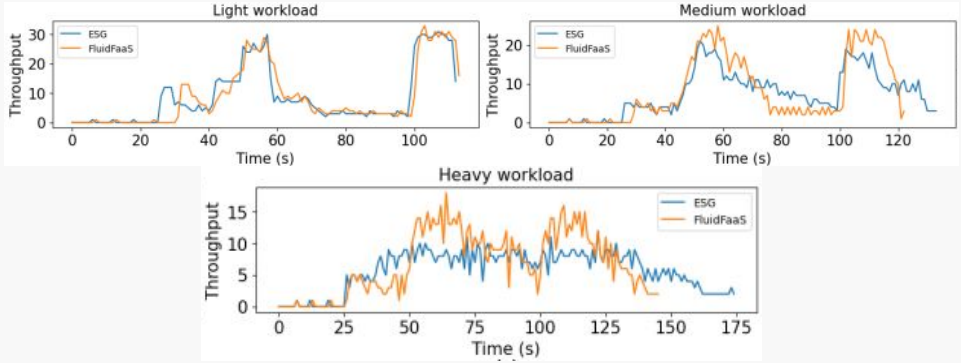


Figure: Throughput in different workloads

P95 Latency:

- 83.3% lower for depth recognition (App 1)
- ≥50% lower for other applications
- Overall: up to 81% reduction (heavy), 70% (medium)

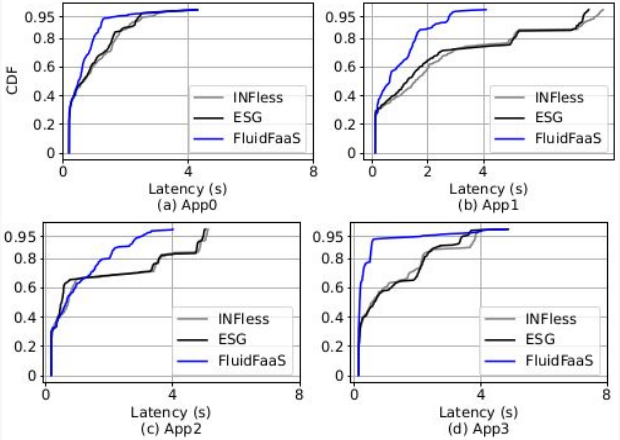


Figure: End-to-end latency distribution in the heavy workloads for each application

Improved GPU Utilization with FluidFaaS

In heavy workloads, FluidFaaS achieves 75% higher utilization than ESG

- Medium workloads: +25% higher
- Light workloads: similar across all systems

Why?

- ESG can only use large MIG slices (e.g., 4g.40gb)
- FluidFaaS utilizes all slices (4g, 2g, 1g) via DAG pipelining

Result:

- Tasks complete 17% faster in heavy workloads
- Less queuing, more throughput, better GPU efficiency

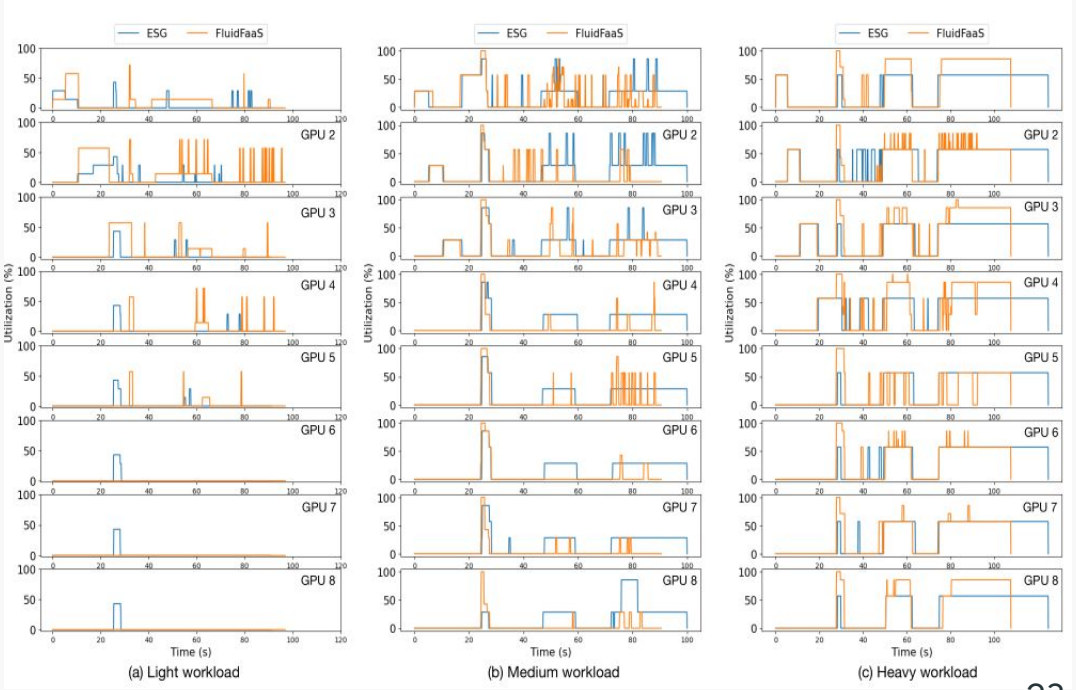


Figure: GPU utilization in different workloads

End-to-End Latency Breakdown

Workload Behavior:

- Light workload: FluidFaaS and ESG perform similarly (both meet SLOs)
- Medium & heavy workloads: FluidFaaS shows up to 2.36× lower latency

Why FluidFaaS is Faster:

- Slightly higher data transfer overhead (10–40ms)
- But much lower queuing delay (up to 3× shorter than ESG)
- Pipelines allow faster response despite stage-wise execution

Net Benefit:

- Reduced queuing outweighs transfer overhead → higher SLO compliance

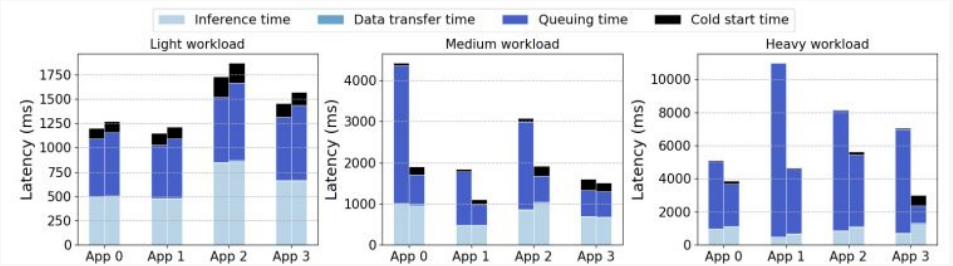


Figure: End-to-end latency breakdown. Left bar is for ESG and right one is for FluidFaaS

05 Conclusion & Takeaways

Conclusion & Takeaways

Problem:

- MIG-based GPU sharing suffers from fragmentation and rigid allocation
- Serverless workloads need dynamic, fine-grained GPU usage

FluidFaaS Solution:

- Enables pipeline-based execution across fragmented MIG slices
- Introduces hotness-aware eviction for time-sharing without compromising isolation

Results:

- Up to 90% higher SLO hit rate
- 75% higher throughput, 81% lower P95 latency
- Significant GPU time savings vs. ESG and INFless

Key Takeaway:

- FluidFaaS achieves high resource efficiency and performance in serverless ML inference by embracing flexible, runtime-adaptive GPU scheduling

Thanks!