Dynamic Space–Time Scheduling for GPU Inference

Paras Jain, Simon Mo, Ajay Jain[§], Alexey Tumanov,
Joseph Gonzalez, Ion Stoica

riselab UC Berkeley § MIT

Contact Paras Jain
paras_jain@berkeley.edu

Background/Context:

- ML inference increasingly important for soft real–time latency–sensitive applications

Problem:

- Model complexity increases —>latency increases; too slow for soft–real time applications
- GPU —>more attractive for inference, suffers low utilization (under latency constraints)

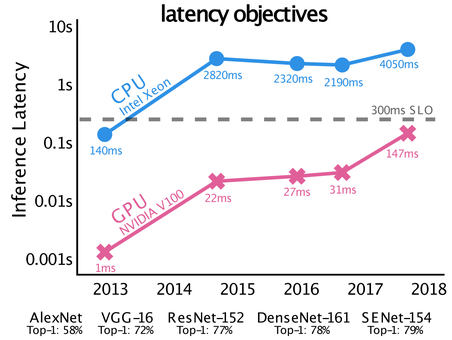
Solution:

- *State of the art*: temporal multiplexing
- *Proposal*: multiplex GPUs across multiple models and time

Motivation: Online inference leads to low GPUs utilization

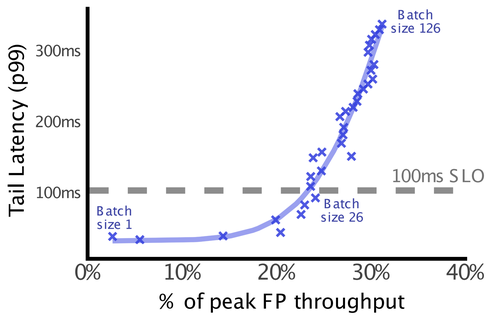
- Due to growing DNN model complexity, **CPUs cannot meet online inference latency requirements**

As models continue to grow, GPUs are the only way to meet online inference latency objectives



- Small batches common in inference leads to **poor GPU utilization** and **low resource–efficiency**

GPUs are under–utilized in online inference due to small batch–sizes



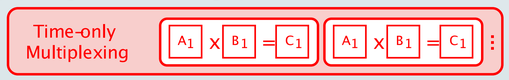
- We explore **spatial and temporal multiplexing** techniques to improve **GPU utilization**

Key requirements for GPU kernel multiplexing

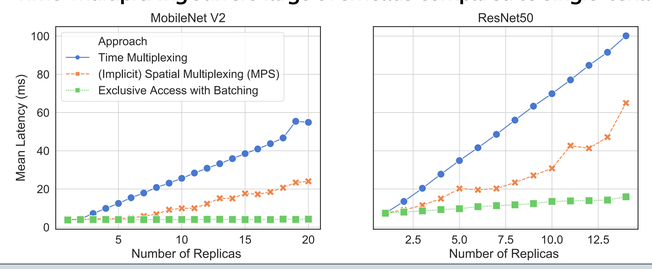
- Runtime performance must be **predictable**
- Multiplexing should increase **resource–efficiency**
- Models on a single GPU should have **inter–tenant isolation**

Time–only multiplexing: poor resource–efficiency

- **Time–multiplexing**: on device scheduler enables interleaved execution of multiple CUDA contexts (no parallel execution)
- **Pro:** Guaranteed isolation between tenants and predictability
- **Con:** Sharply degraded throughput and increased latencies

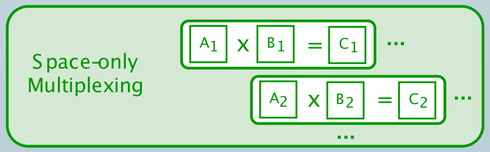


Time–multiplexing suffers large overheads compared to single–tenancy

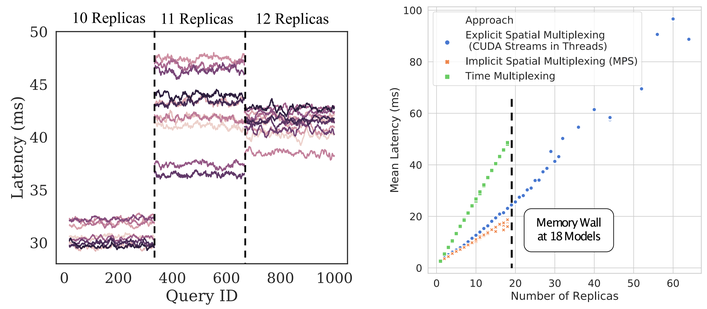


Space–only multiplexing: poor predictability and isolation

- Spatial–multiplexing: NVIDIA Multi–Process Service to partition kernel launches across multiple CUDA Streams
- **Pro:** Kernels can execute in parallel
- **Con:** Unpredictable performance and lack of isolation

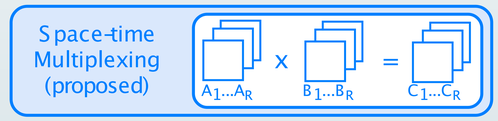


Left: As we add replicas, space multiplexing latencies are unpredictable
Right: Time–multiplexing and NVIDIA MPS cannot scale past 18 tenants

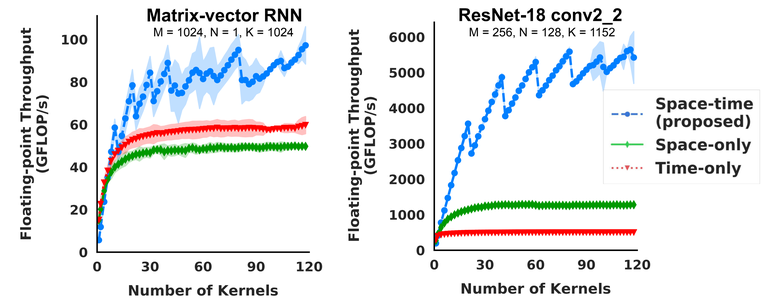


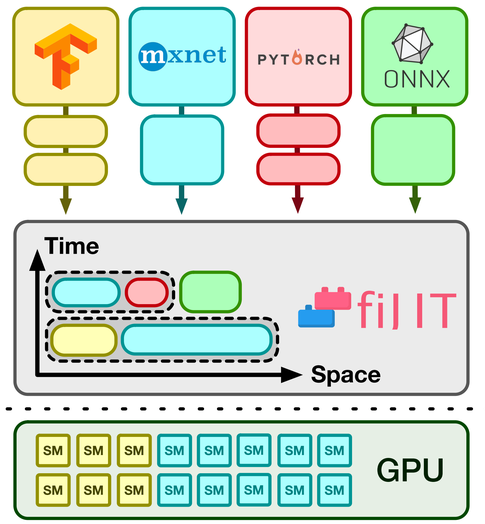
Proposed solution: Space–and–Time multiplexing

- **Space–Time scheduling:** Inter–model kernel batching via a software scheduler
- **Key idea: provide isolation via software**



Space–time multiplexing achieves higher FP32 throughput compared to current approaches (space or time only).





DNN frameworks dispatch kernels schematics to a JIT compiler

JIT compiler optimizes models for efficiency and latency requirements

GPU achieves high utilization and latency SLO attainment

Conclusions: A large opportunity gap in performance

- There still exists a **7x performance gap** in utilization
- We show that space–time multiplexing can drive up to **2.5x–4.6x** throughput speedups