

Fast GPU Primitives for Multiplexed Deep Learning Inference 🕢 rise 🔾



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Background/Context:

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

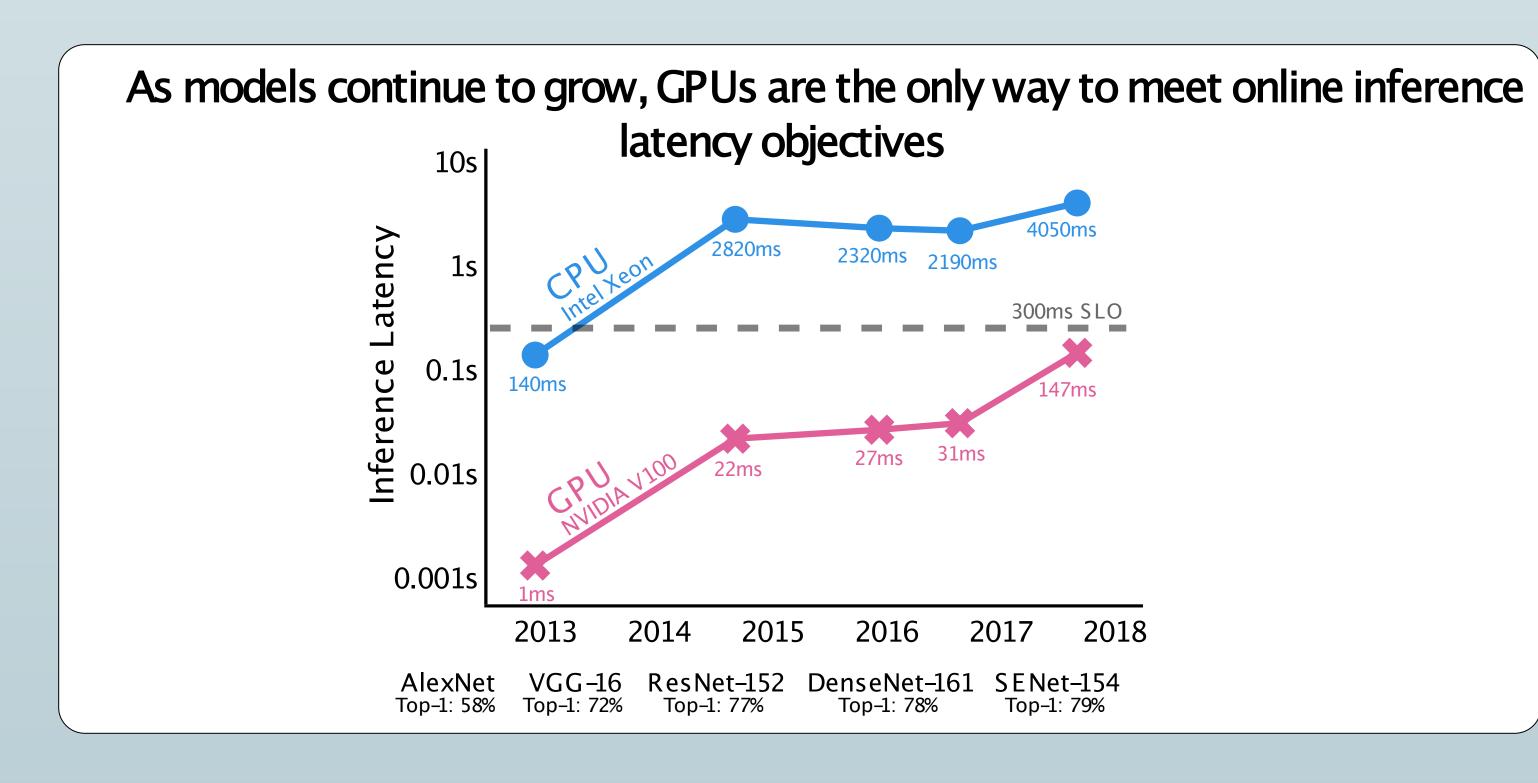
Problem:

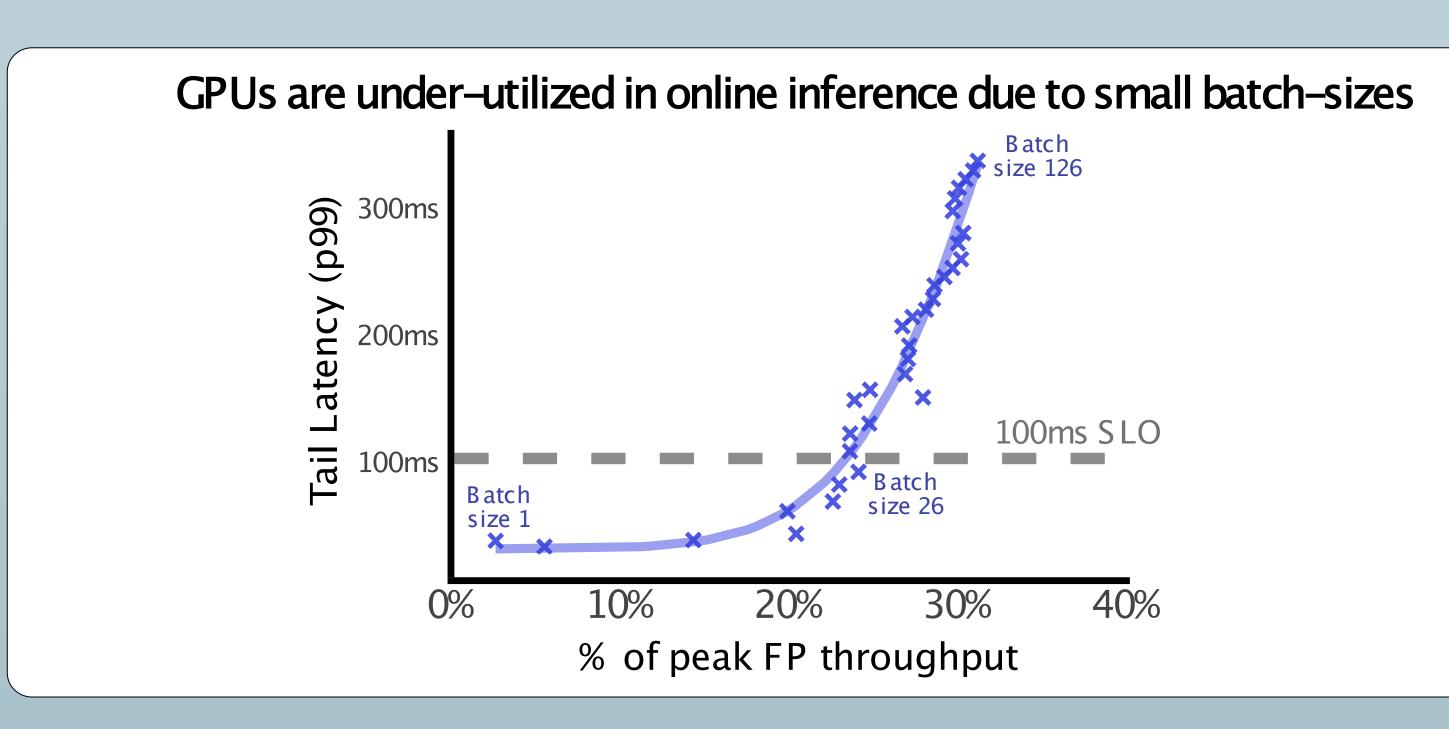
- Model complexity increases > latency increases; too slow for soft-real time applications
- GPU > more attractive for inference, suffers low utilization (under latency constraints)

Solution:

- State of the art: temporal multiplexing
- *Proposal*: multiplex GPUs across multiple models and time
- Approaches: kernel coalescing, kernel constraining
- Goal: VLW inspired JIT compiler that enables serverless abstractions for GPU

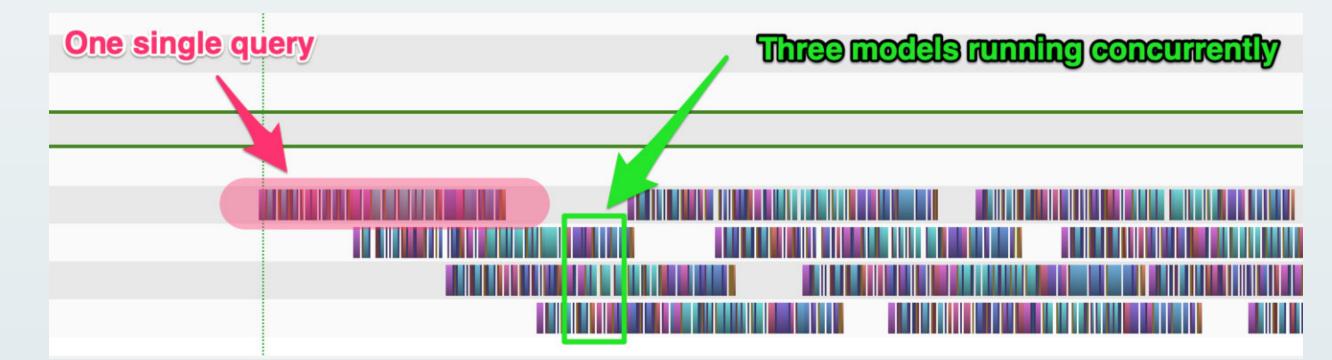
Motivation: Online inference leads to low GPUs utilization



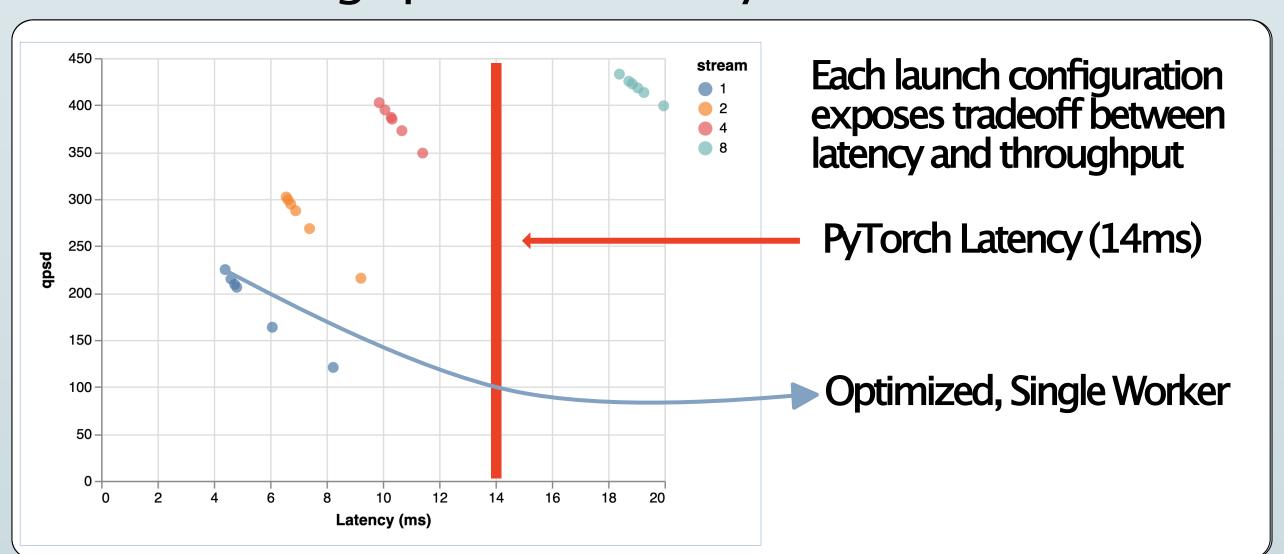


Key requirements for GPU kernel multiplexing

- Runtime performance must be predictable
- Multiplexing should increase resource—efficiency



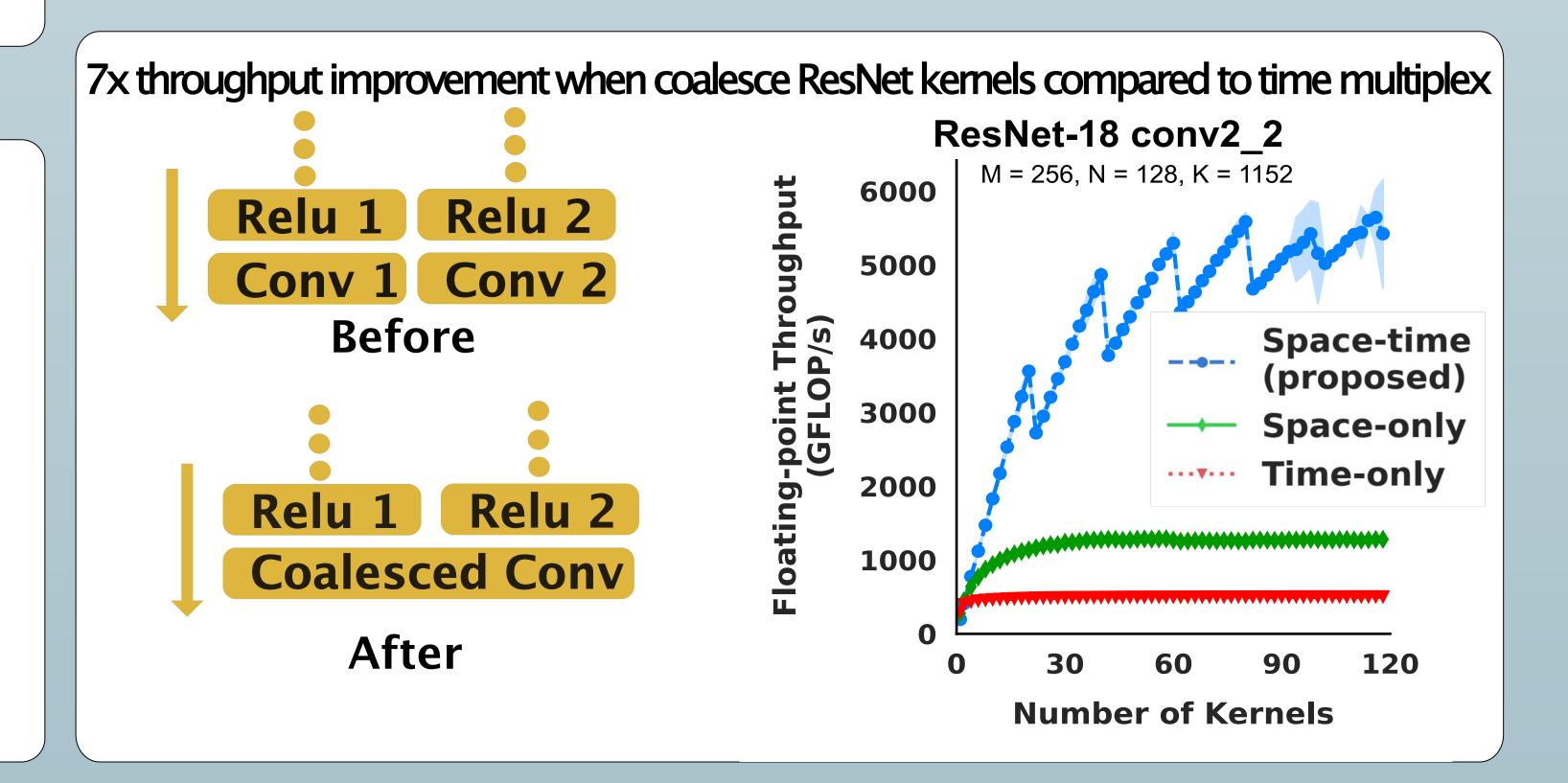
- The runtime should be **fair** to all its tenants:
 - Equal treatment: same SLO guarantees
 - Equal outcome: strict inter-tenant isolation
- Enable throughput vs latency tradeoff



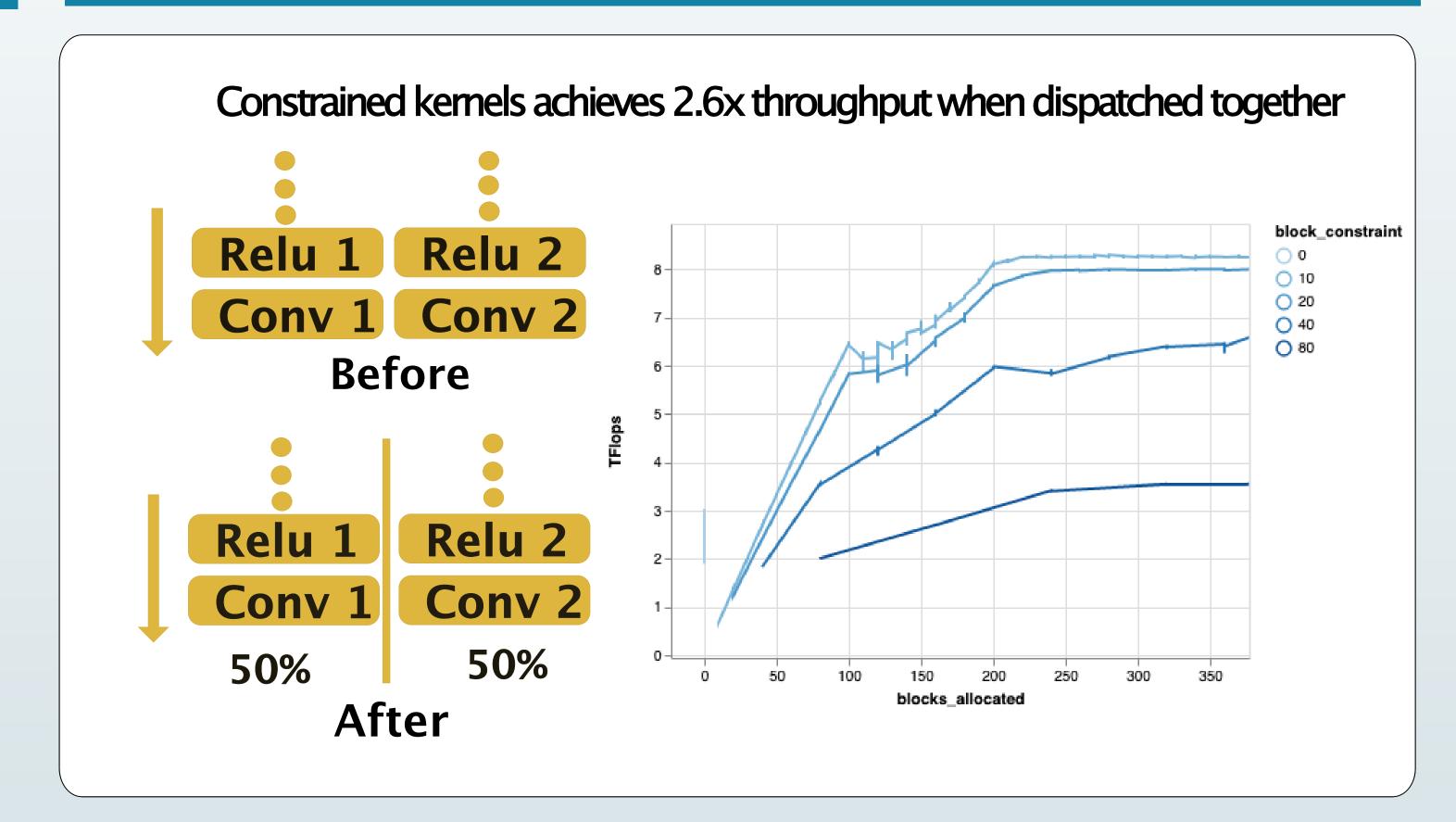
Time-only multiplexing: poor resource-efficiency

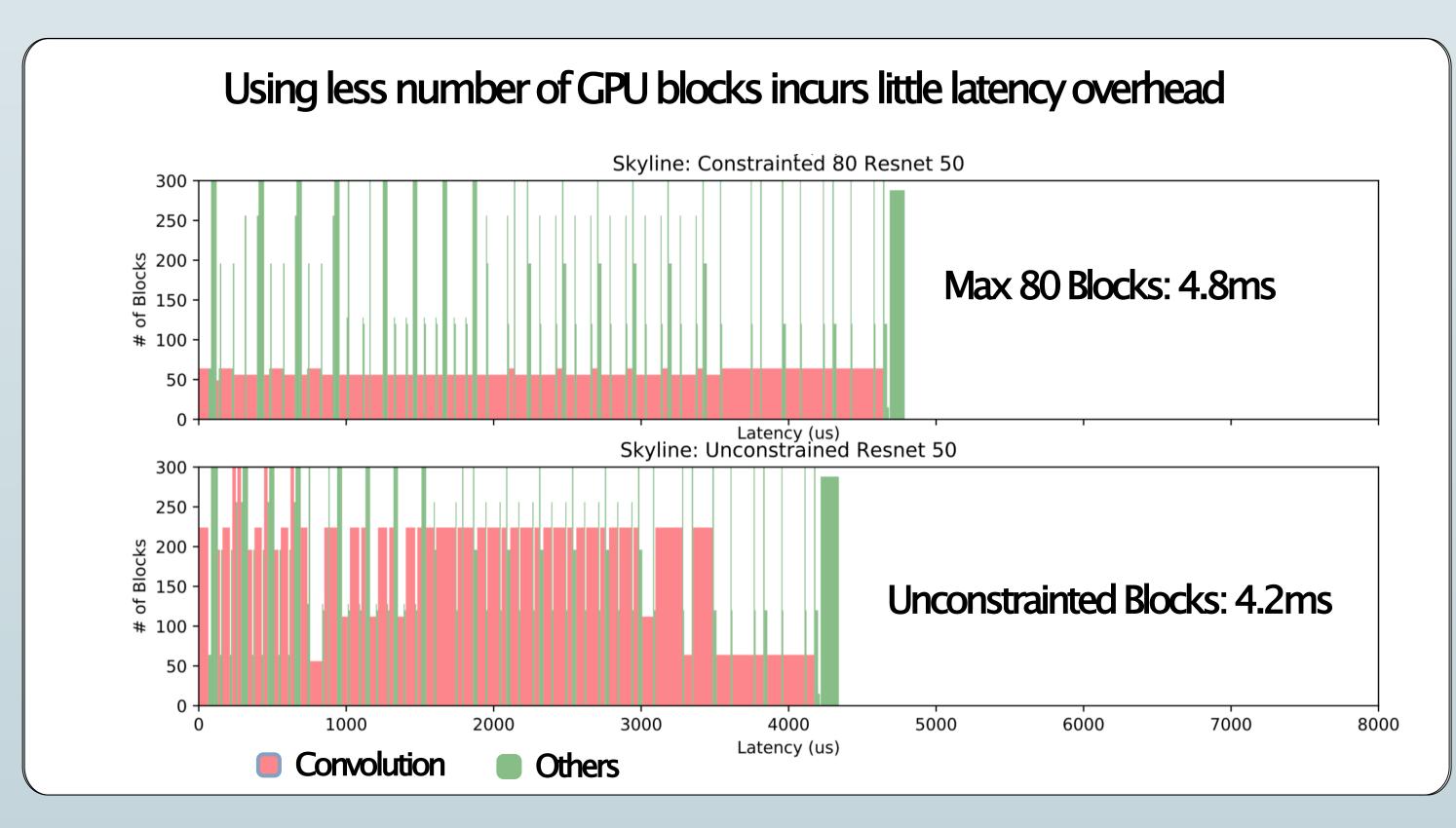
- Time-multiplexing: on device scheduler enables interleaved execution of multiple CUDA contexts (no parallel execution)
- Pro: Guaranteed isolation between tenants and predictability
- Con: Sharply degraded throughput and increased latencies

Space-Time multiplexing: coalesce similar kernels



GPU Partitioning: constraint each kernel to # of blocks





Vision: VLIW JIT Compiler -> Serverless GPU

