Nexus: A GPU Cluster Engine for Accelerating DNN-Based Video Analysis

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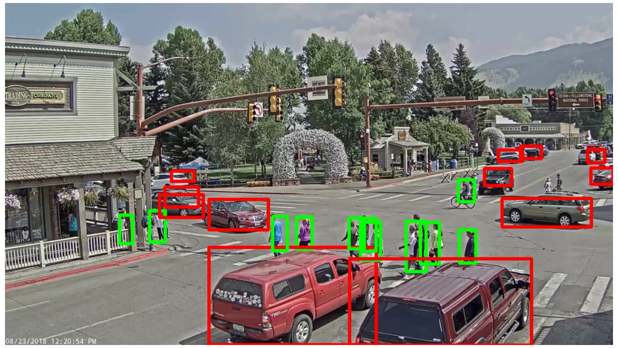
Matthai Philipose, Arvind Krishnamurthy, Ravi Sundaram

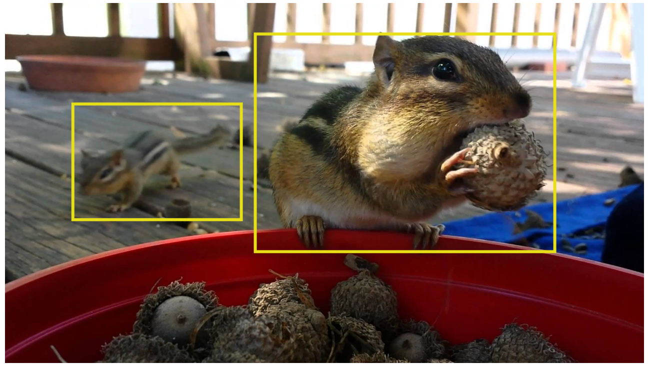
Analyze video at large scale



Real-time traffic monitoring

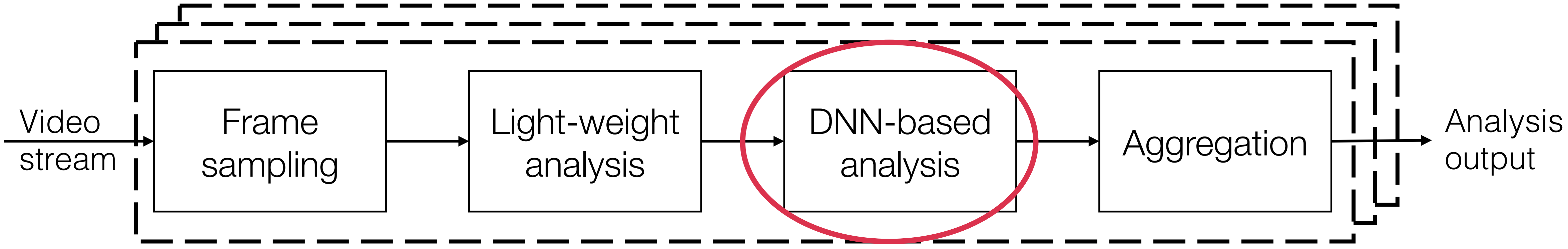
Game stream indexing

Surveillance



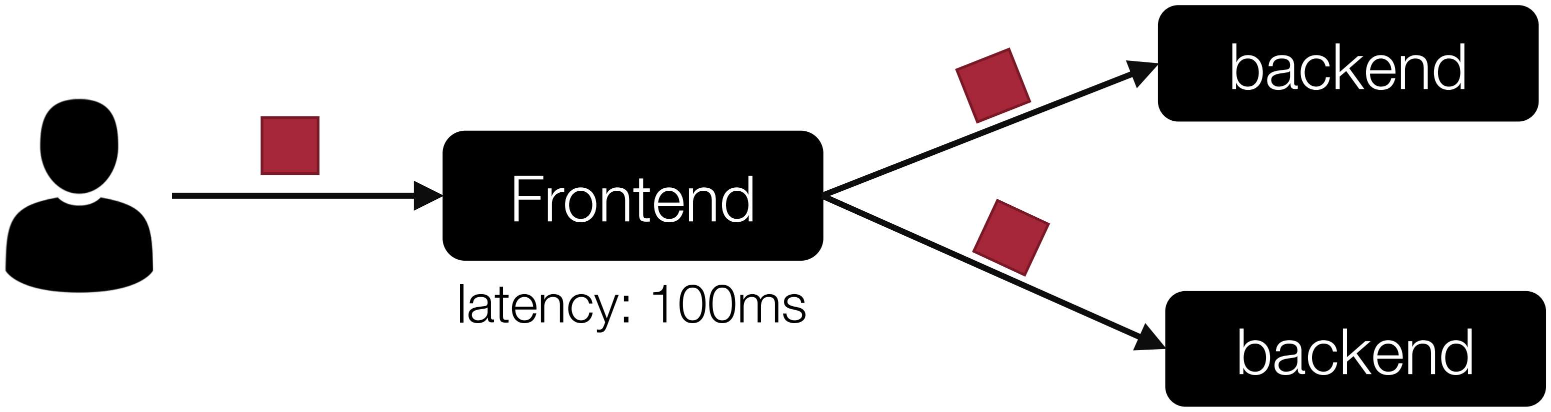
Intelligent family camera

Video analysis pipeline



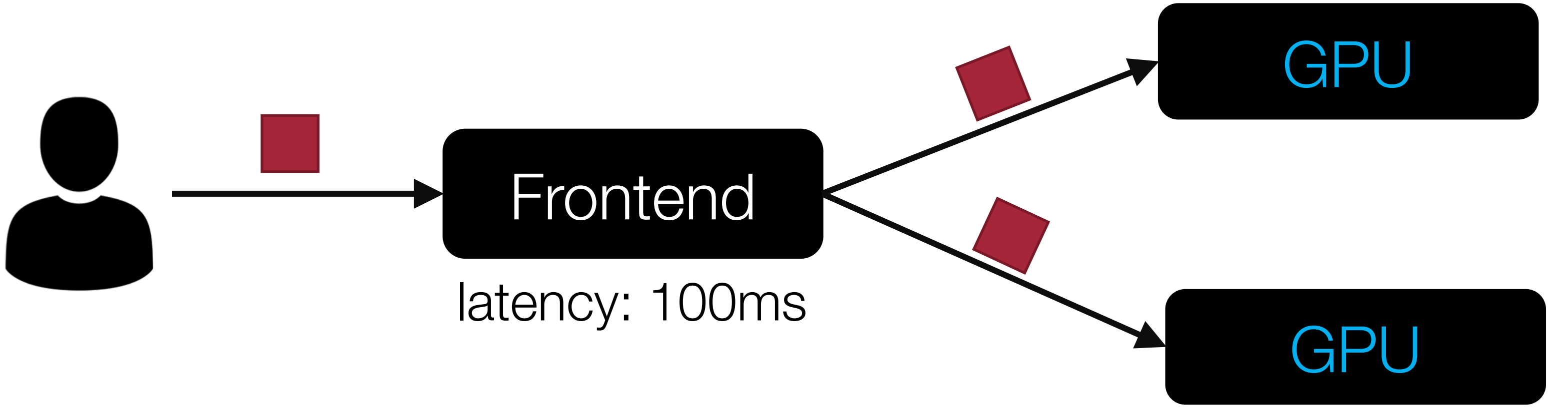
Most computation and cost

DNN serving similar to traditional distributed serving



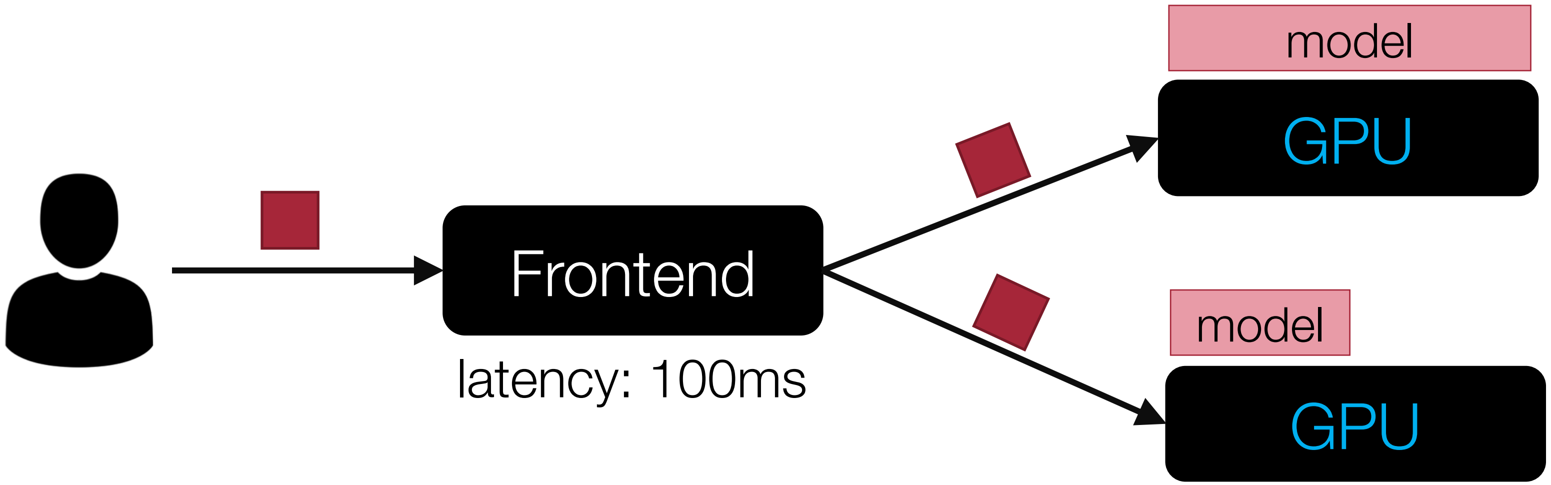
- Auto scaling
- Load balancing
- Latency constraints

DNN serving imposes additional constraints



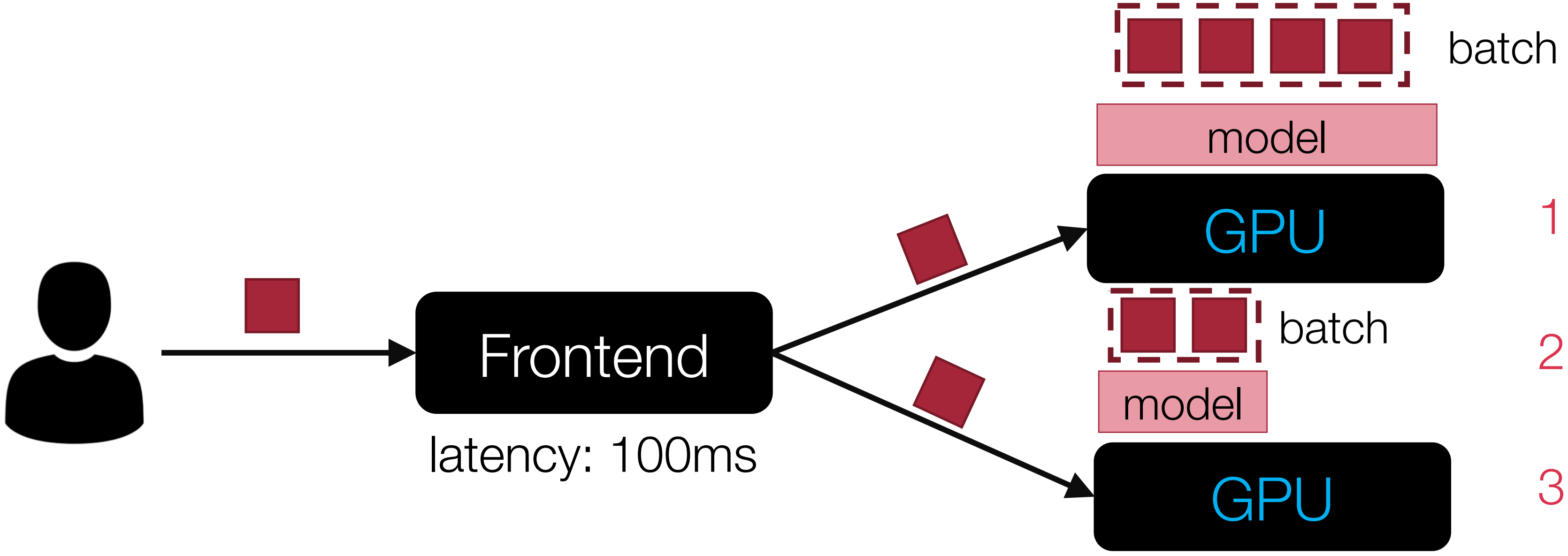
1. Use accelerators

DNN serving imposes additional constraints



1. Use accelerators
2. Pre-load models

DNN serving imposes additional constraints



1. Use accelerators
2. Pre-load models
3. Batch processing

Existing DNN serving systems are single-app solutions

E.g., Tensorflow Serving, Clipper

- Do not coordinate resource allocations across DNN applications
- Rely on external schedulers that cannot perform cross-app optimizations

How to build a serving system that coordinates the serving of multiple DNN applications?

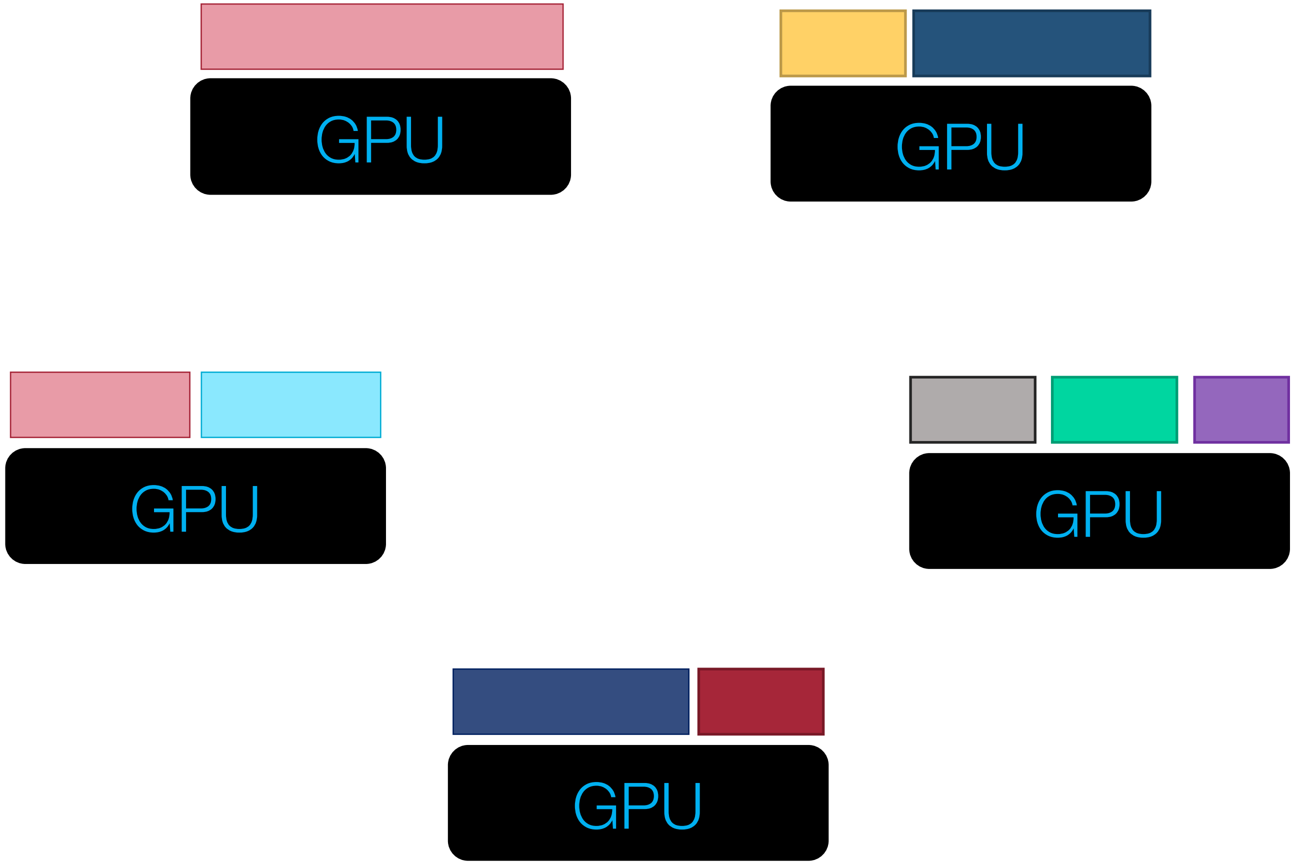
Optimization opportunities

1. Cluster-level: batch-aware, latency-aware resource allocation across models

2. Application-level: handle complex queries

3. Model-level: batch at sub-model granularity

Opportunity 1: cluster-level resource allocation



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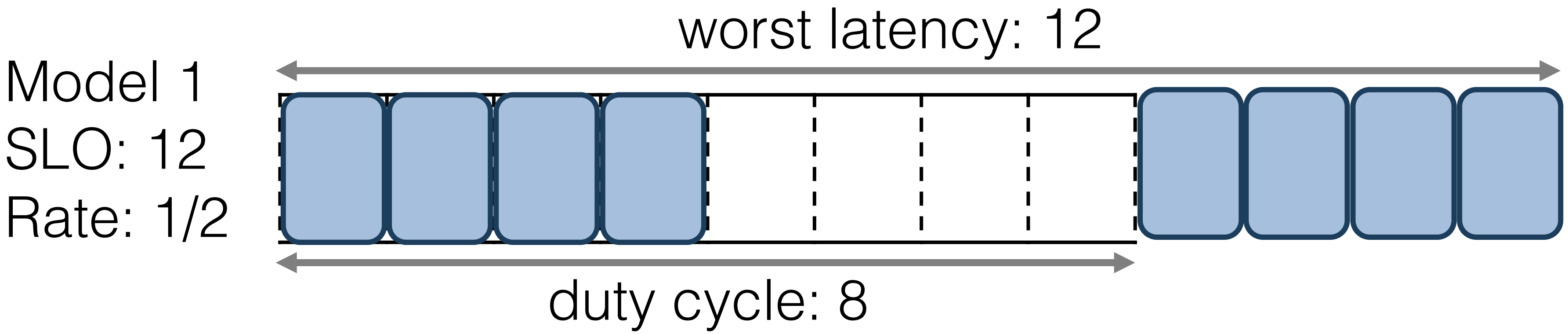

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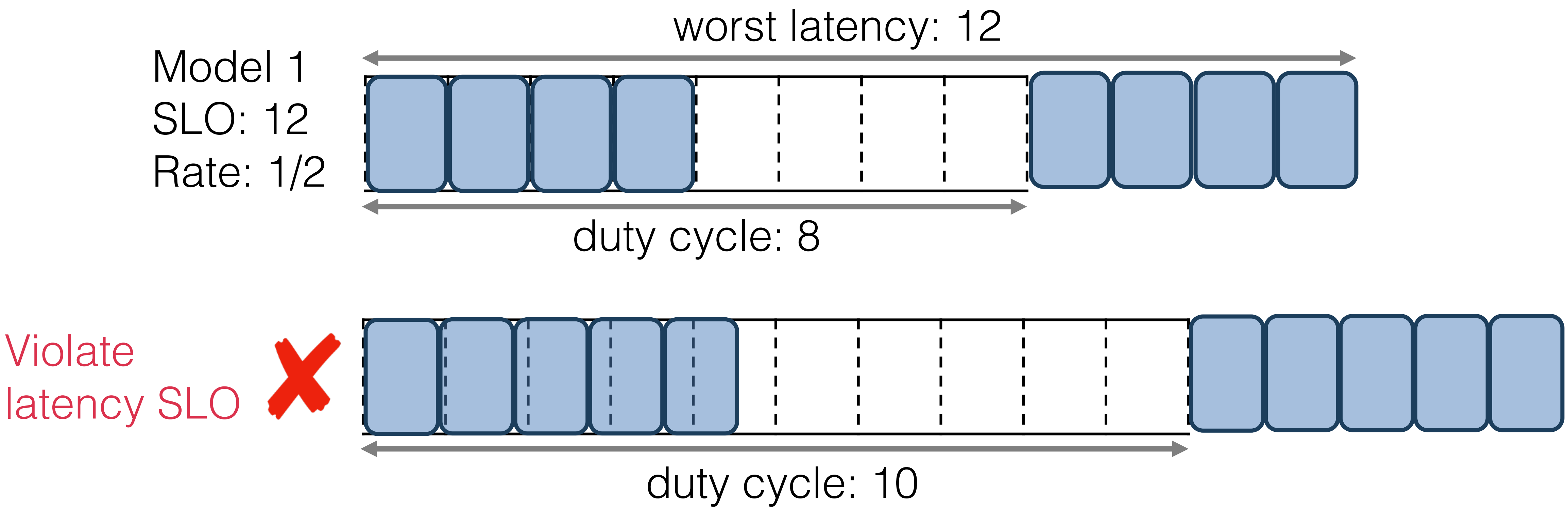
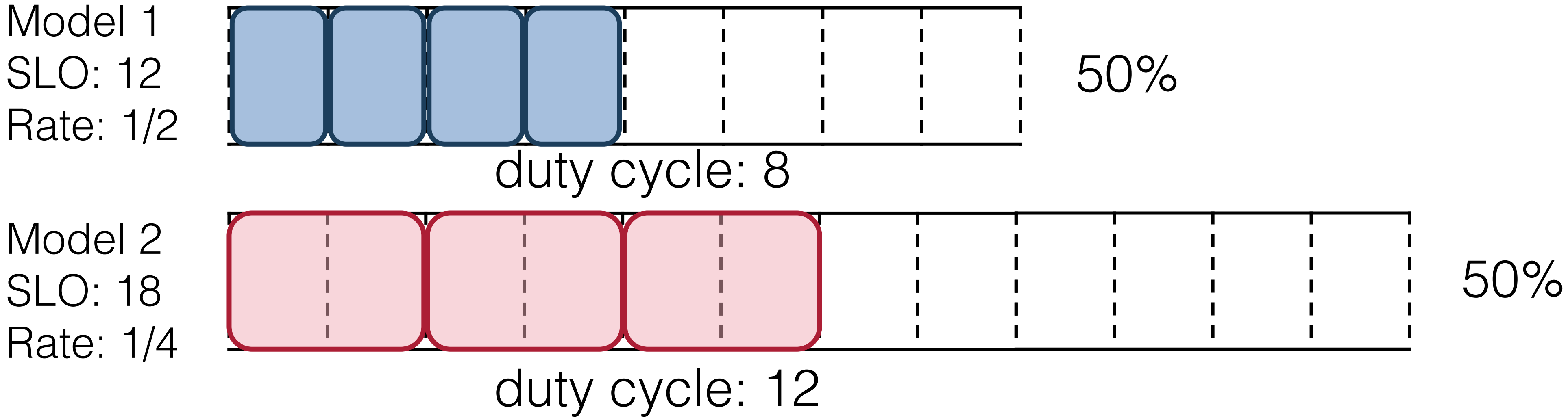


Latency SLO limits the batching optimization

Opportunity 1: cluster-level resource allocation



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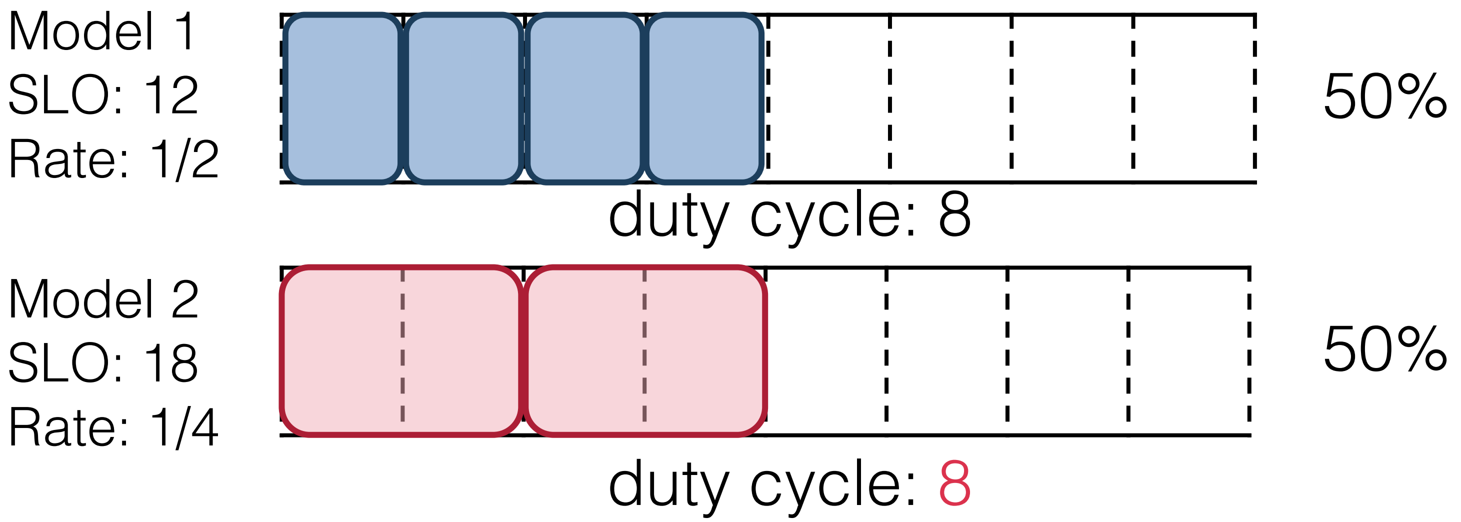

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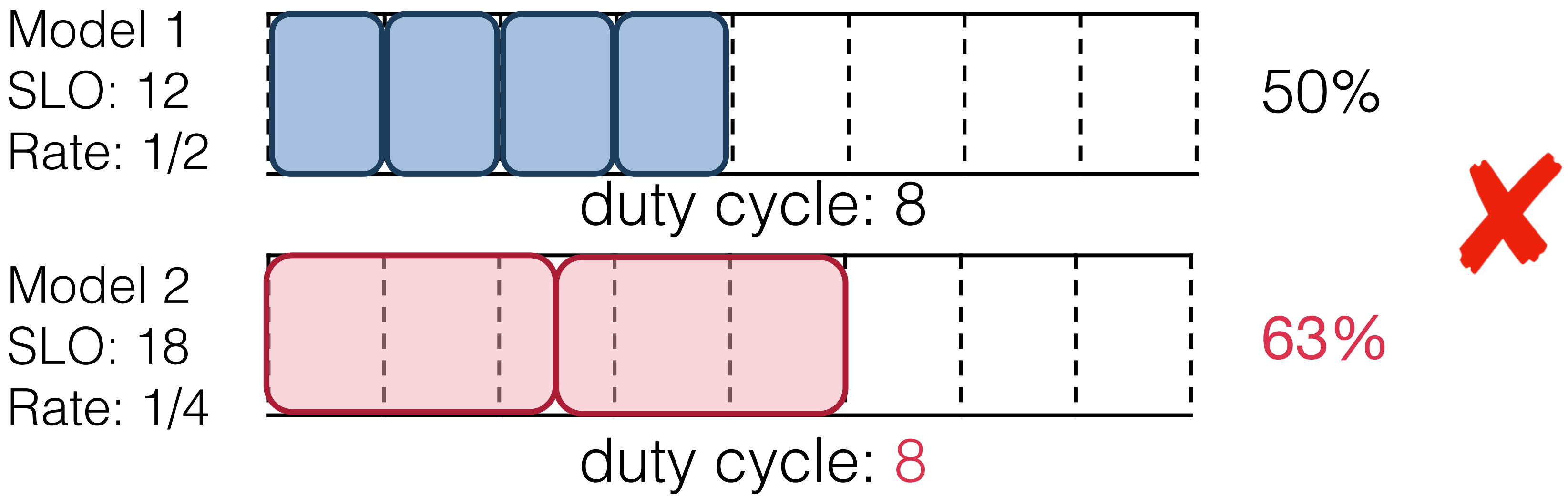
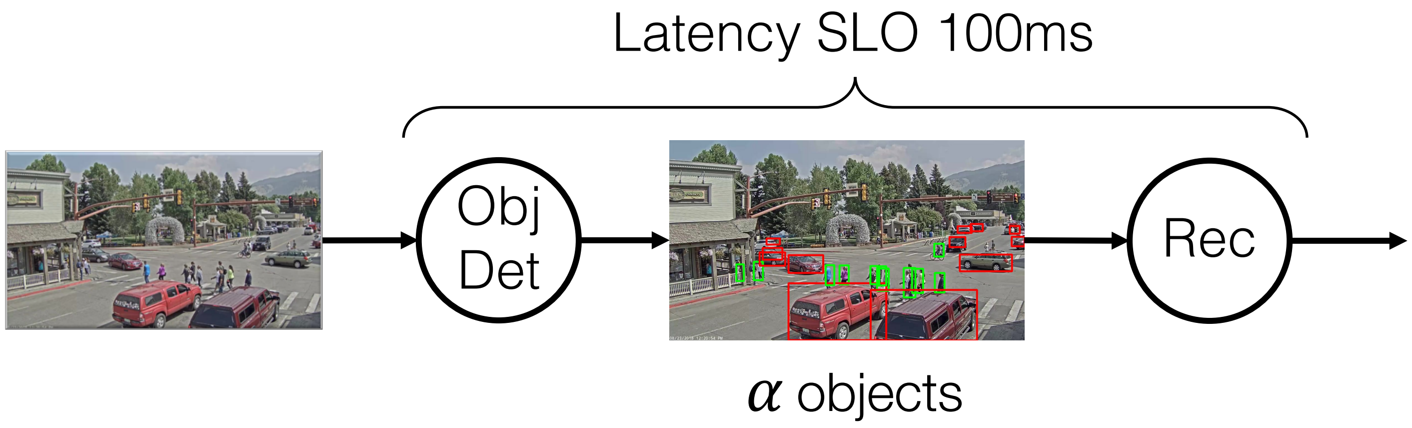


Challenge: GPU sharing has to account for SLO and "squishy" load demands across models

Opportunity 2: app-level complex query



Model Latency SLO (ms)		Throughput (reqs/s/GPU)		
Detection	Recognition	$\alpha = 0.1$	$\alpha = 1$	$\alpha = 10$
40	60			
50	50			
60	40			

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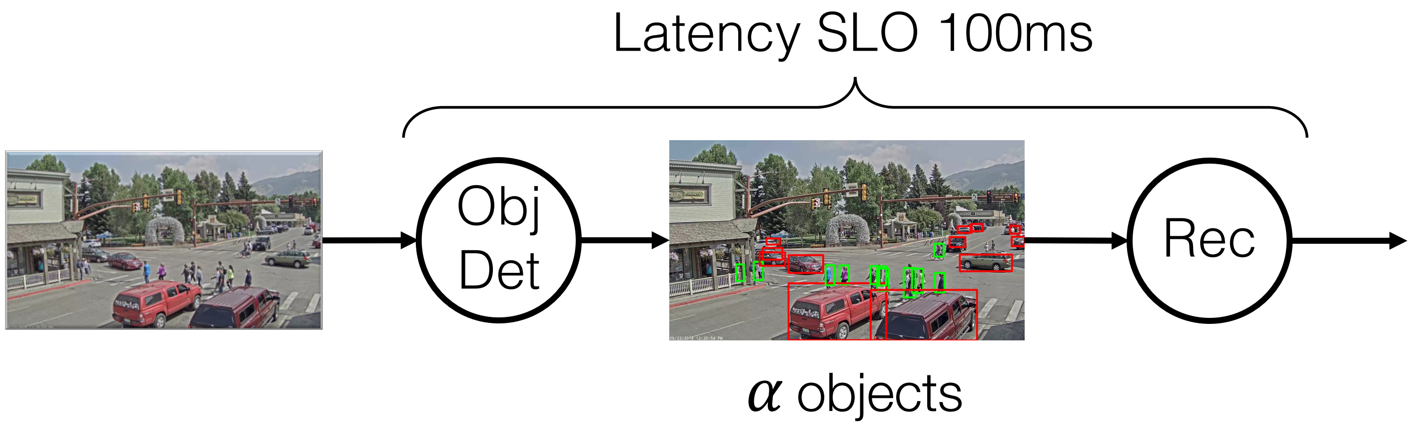
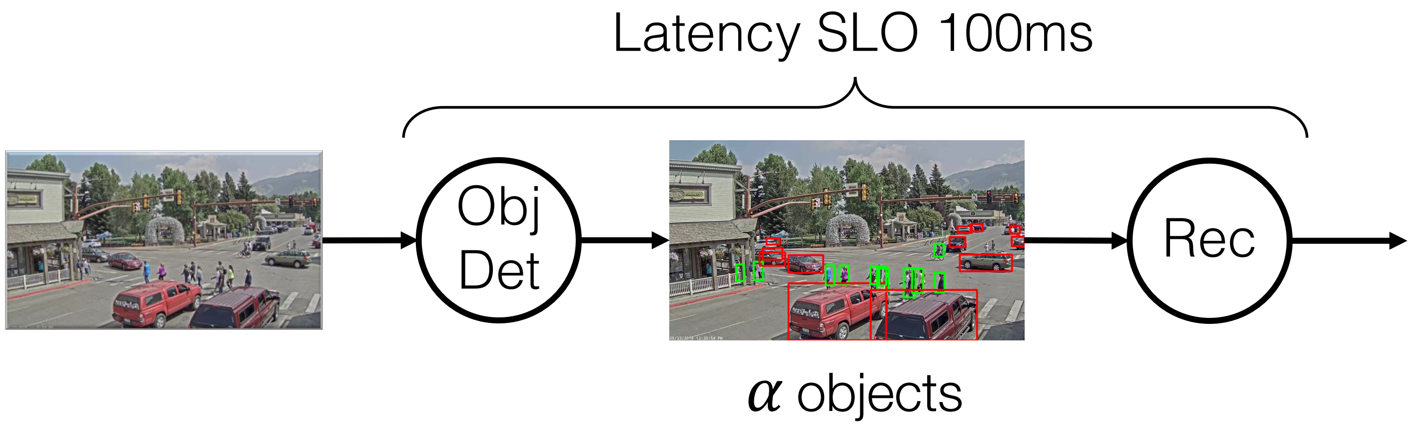


Model Latency SLO (ms)		Throughput (reqs/s/GPU)		
Detection	Recognition	$\alpha = 0.1$	$\alpha = 1$	$\alpha = 10$
40	60	Low	Medium	High
50	50	Medium	High	Medium
60	40	High	Medium	Low

Opportunity 2: app-level complex query



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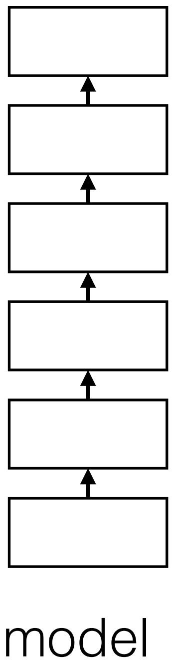
Challenge: Latency split impacts efficiency and needs to be adapted to workload

Opportunity 3: model-level transfer learning

- Fine-tune a model to a different dataset or task



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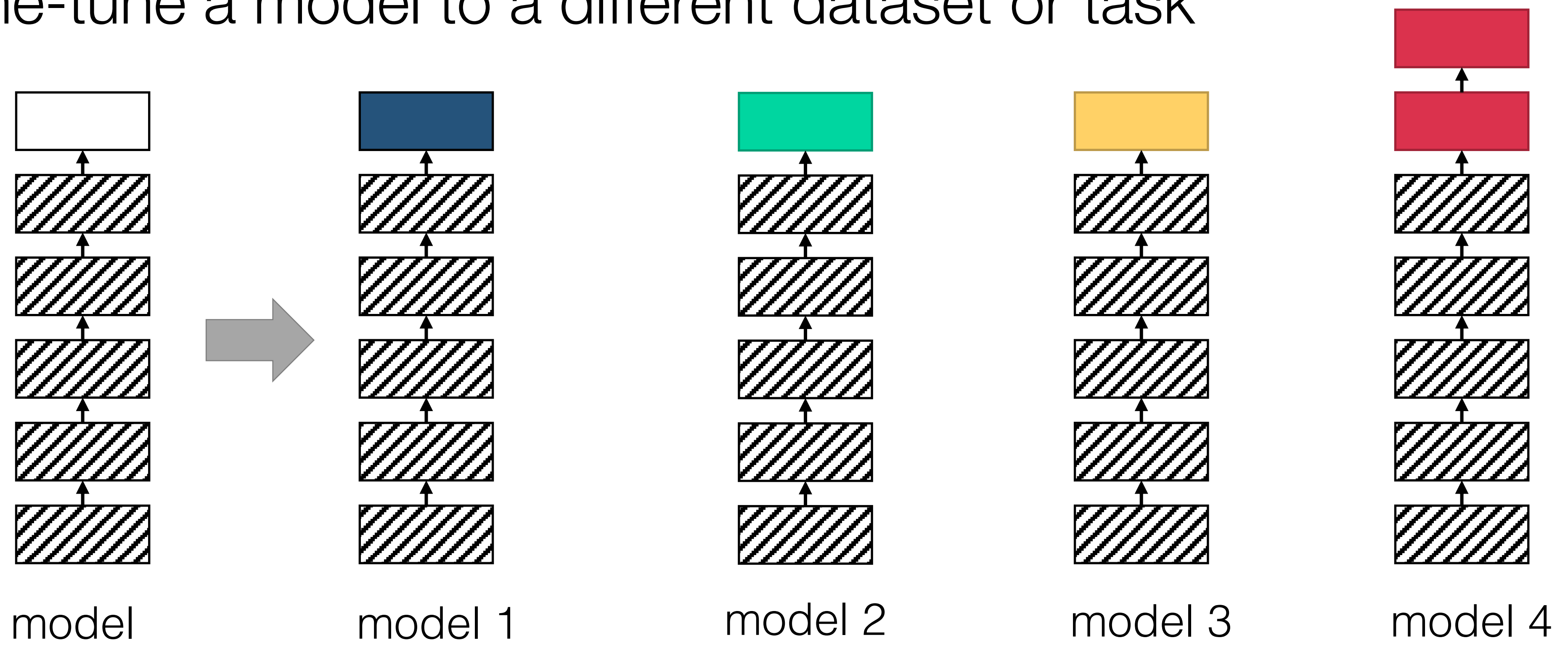

Challenge: How to speed up the common part across models?

Nexus: efficient and scalable DNN execution system on GPU cluster

1. Profiling-based batch-aware resource allocator

2. Query analyzer determines latency split given latency SLO

3. Batch common prefix across models

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Resource allocation problem

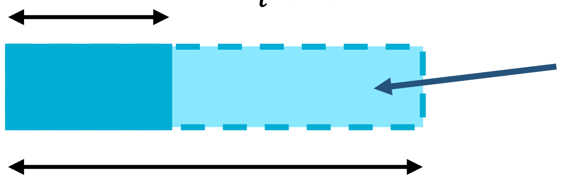
- Bin-packing problem: pack model sessions (model, SLO) to GPUs
- Optimization goal: minimize total number of GPUs
- Constraint: requests need to be served within latency SLOs
- More complex than bin packing due to
    - Change the batch size (squishy tasks)
    - Need to meet latency SLO

Squishy bin-packing algorithm

1. Allocate one GPU for each model session, and choose largest batch size b_i such that $d_i + l_i(b_i) \leq L_i$

exec latency $\ell_{k_i}(b_i)$

Model M_i



Extra cycles to fit in other models

duty cycle $d_i = b_i / r_i$

2. Merge these nodes into fewer nodes
   Maintain two invariants:
   - Duty cycles will never increase
   - Occupancy of combined nodes ≤ 1

How to merge two nodes?
Which nodes to merge?

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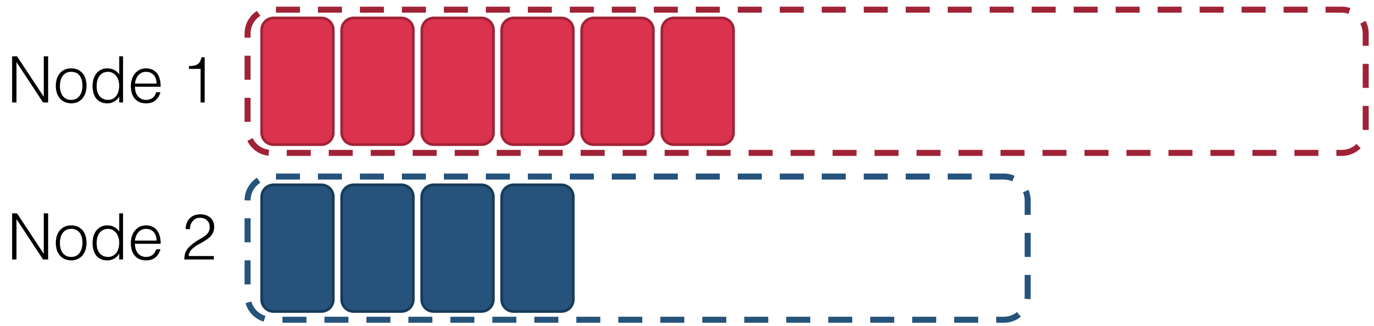

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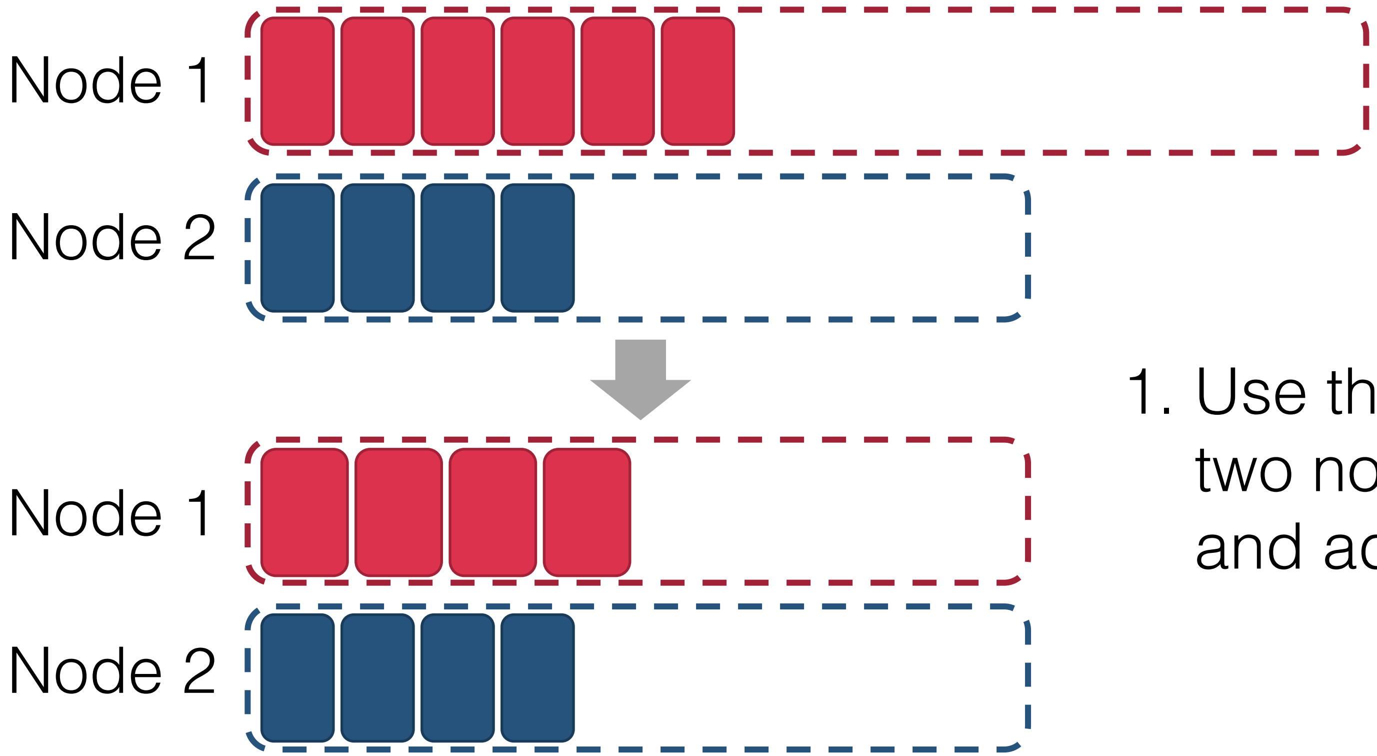
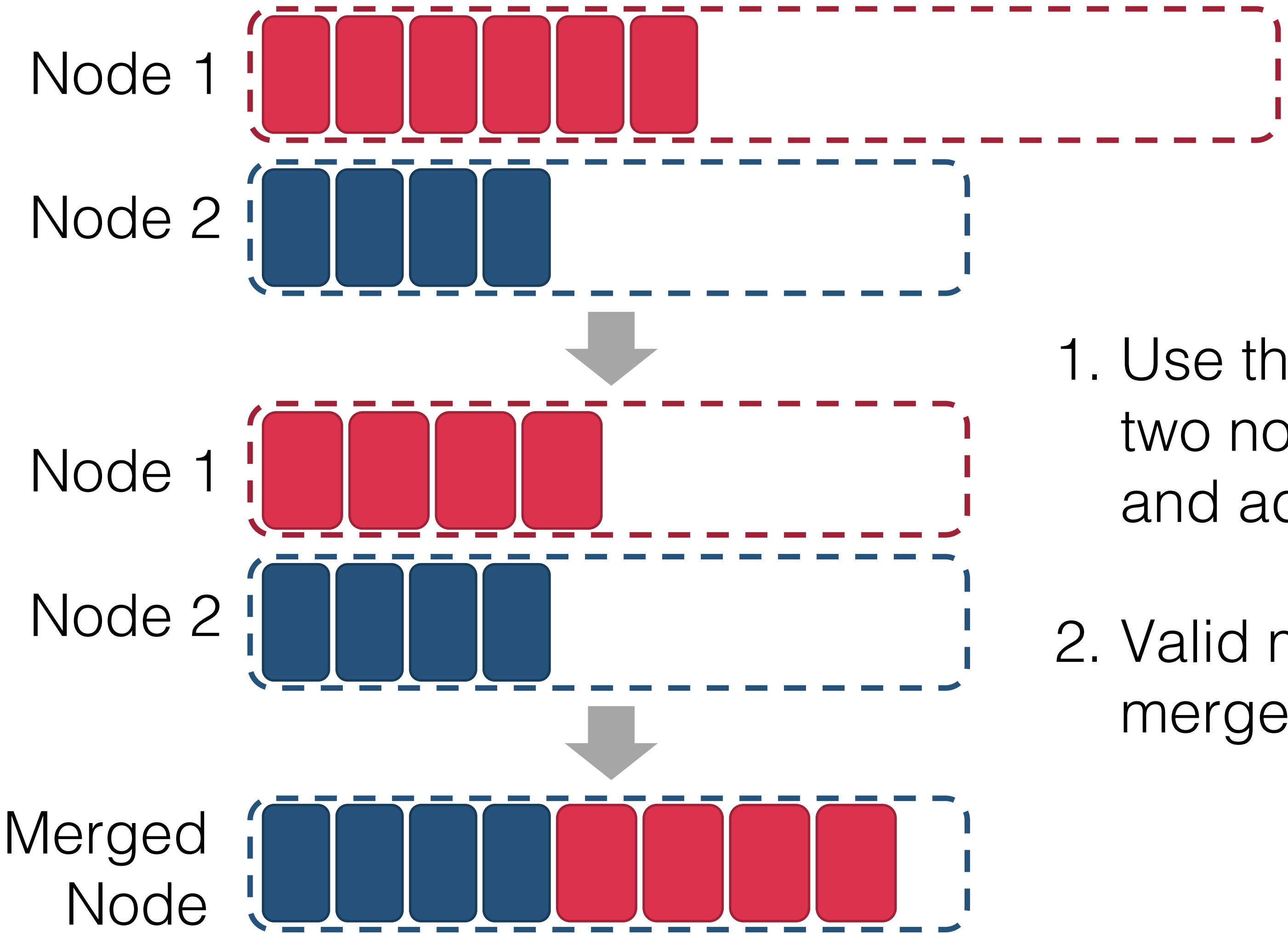


1. Use the minimum duty cycle of two nodes as the new duty cycle, and adjust batch size

How to merge two nodes?



1. Use the minimum duty cycle of two nodes as the new duty cycle, and adjust batch size

2. Valid merge if occupancy of merged node is no more than 1

Which nodes to merge?

- Sort all nodes by its occupancy in decreasing order
- For each node
  - Find a merging that yields highest occupancy
  - Otherwise, add this node in the scheduled nodes

Nexus: efficient and scalable DNN execution system on GPU cluster

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Query Analysis

Given: query latency SLO L, request rate for model u as R_u, and max throughput of model u with time budget t as $\mathrm{TP}_u(t)$

Goal: minimize the total number of GPUs

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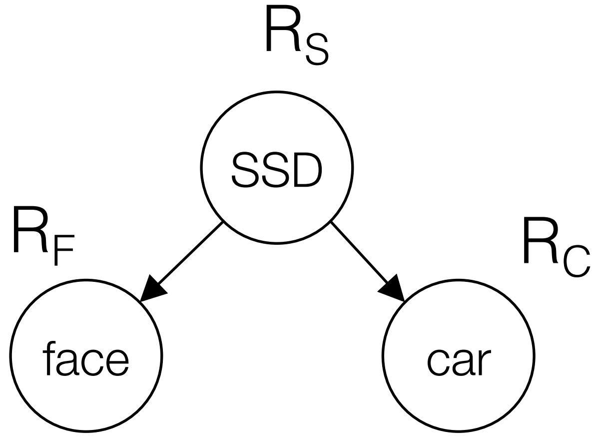
Goal: minimize the total number of GPUs

1. Extract the dataflow dependency graph between model invocations



Traffic app

Query Analysis

Given: query latency SLO L, request rate for model u as R_u, and max throughput of model u with time budget t as $\mathrm{TP}_u(t)$

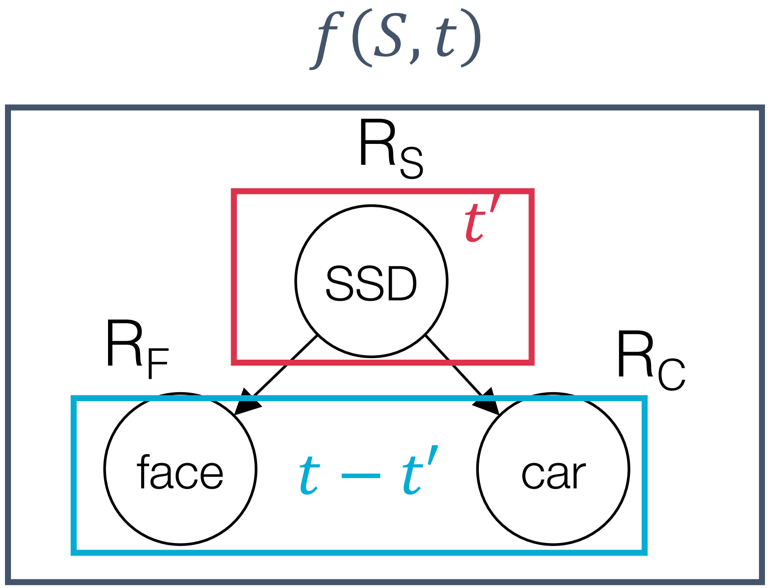
Goal: minimize the total number of GPUs

2. Use the dynamic programming

   Define function $f(u,t)$ as the min #GPUs required to run model u and subtree of u within time budget t

$$f(u,t) = \boxed{\min_{t' \le t}} \left(\underbrace{\boxed{R_u/\mathrm{TP}_u(t')}}_{\text{\#GPUs for SSD}} + \underbrace{\boxed{\sum_{v:M_u \to M_v} f(v, t-t')}}_{\text{\#GPUs for subtrees (face, car)}} \right)$$

   result is $f(root, L)$



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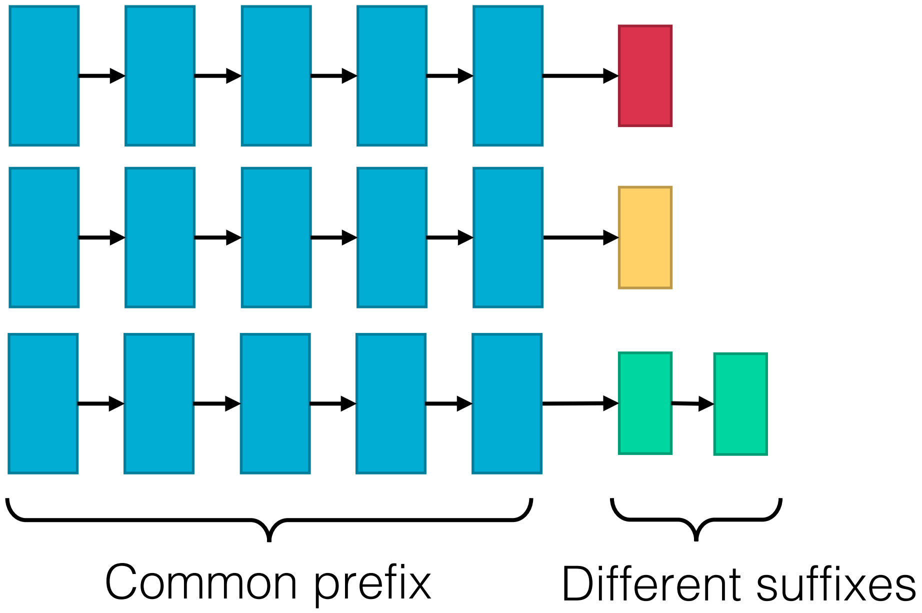
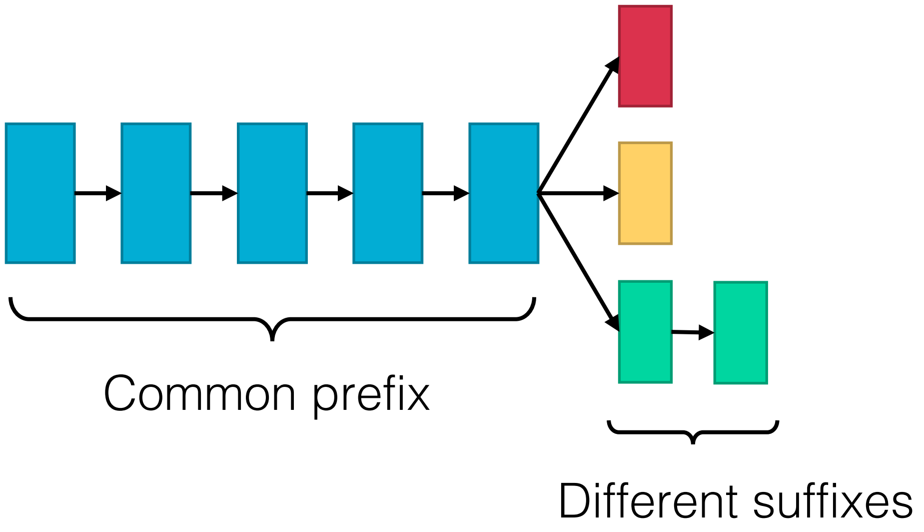
Prefix batching for transfer learning

- Compute the hash of sub-tree and detect common sub-trees



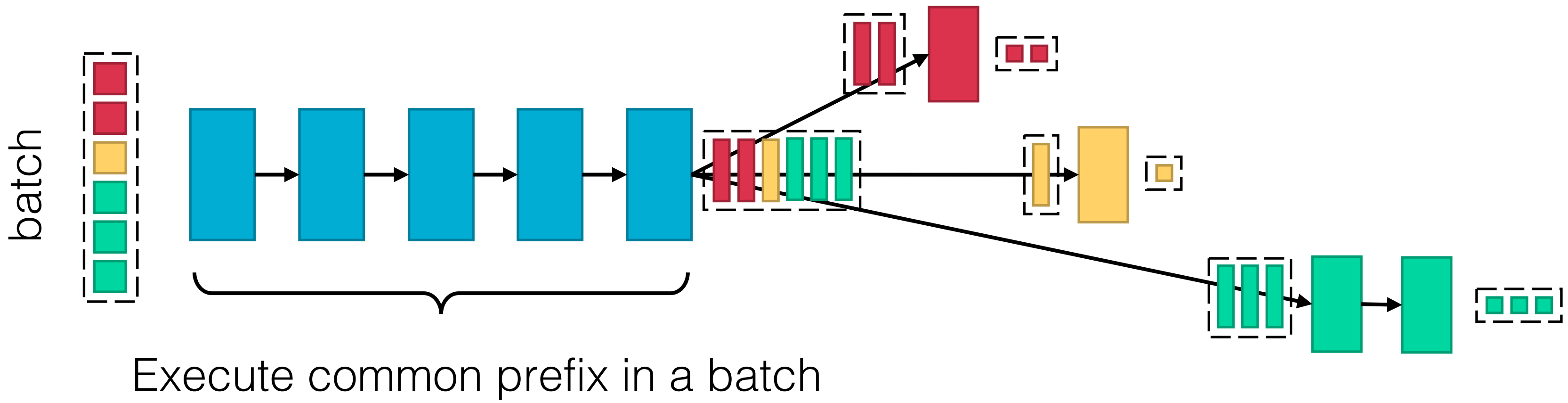
Prefix batching for transfer learning

- Compute the hash of sub-tree and detect common sub-trees
- Load common prefix once and different suffixes



Prefix batching for transfer learning

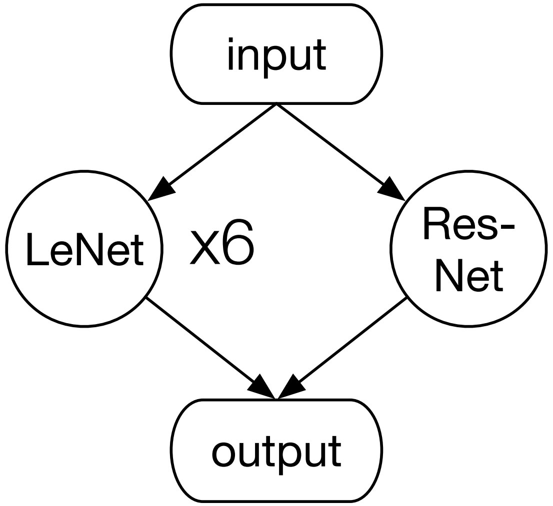
- Compute the hash of sub-tree and detect common sub-trees
- Load common prefix once and different suffixes
- Execute common prefix in a batch of mixed requests and execute different suffixes sequentially



Evaluation

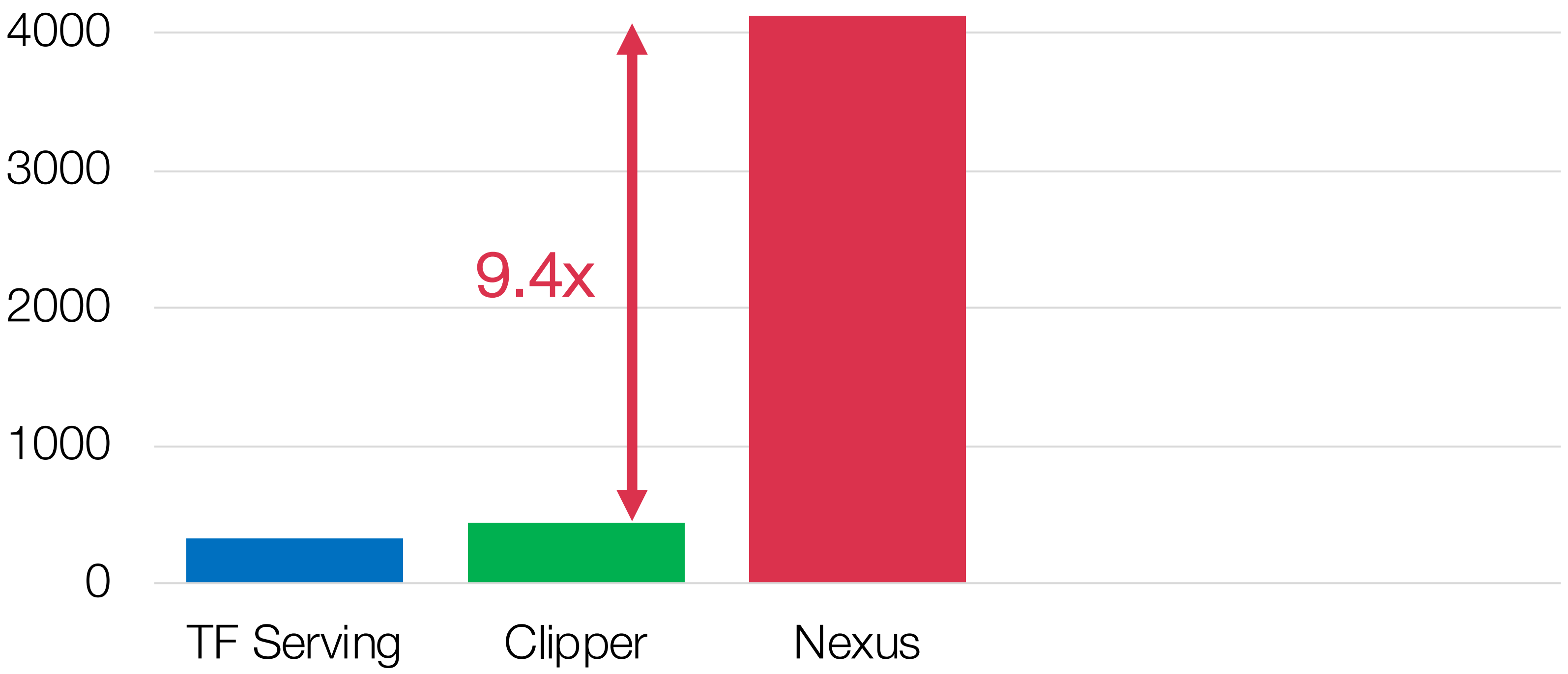
- Baseline: Clipper and Tensorflow Serving
- Both lack support for cluster and complex queries
  - Batch-oblivious scheduler
    allocates # GPUs $\propto$ request rate / max throughput under latency SLO on a single GPU
  - Naive query analysis
    splits query latency SLO evenly to each stage

Case study: game analysis



Case study: game analysis

- 20 Games with popularity distribution (Zipf-0.9)
- Specialize ResNet-50 by fine-tuning the last layer for each game
- 16 Nvidia GTX 1080Ti with latency SLO 50ms



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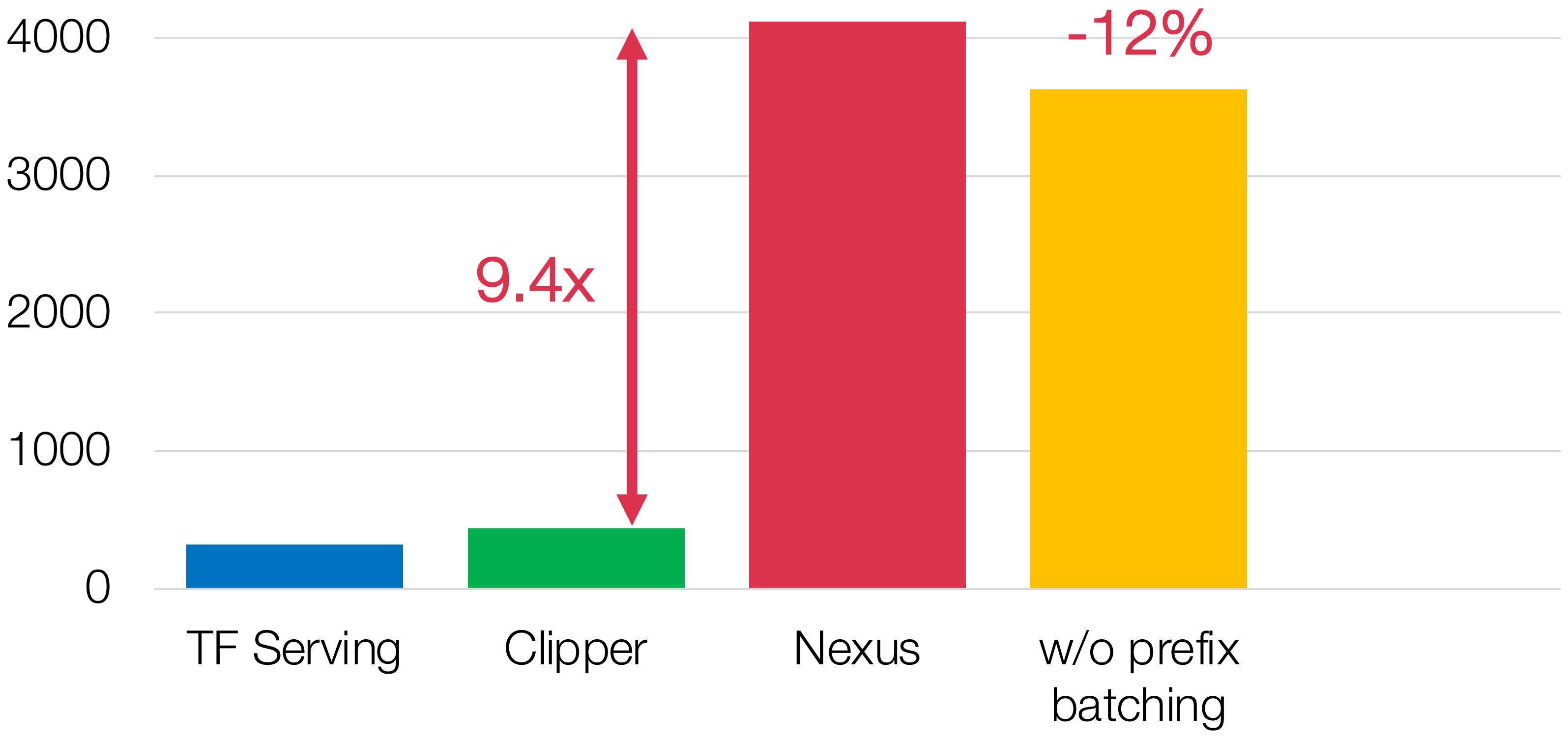

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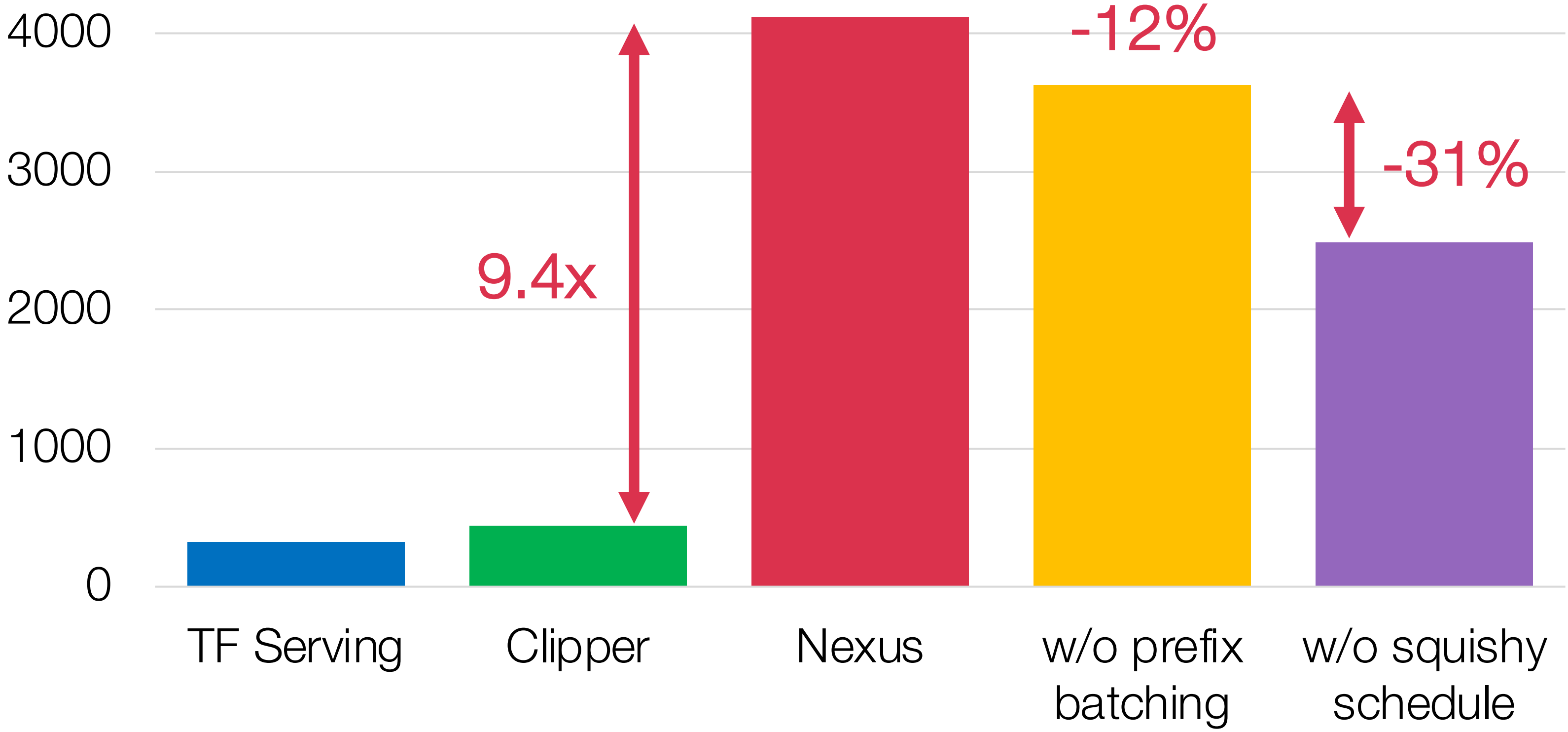
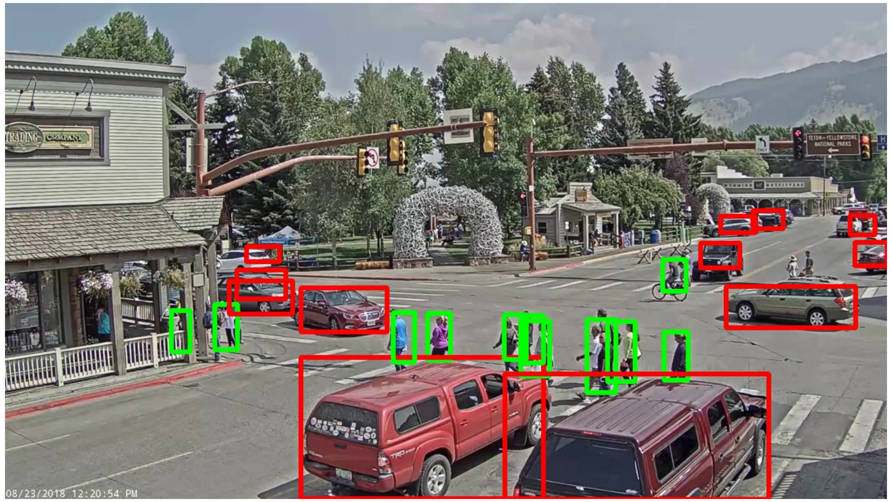
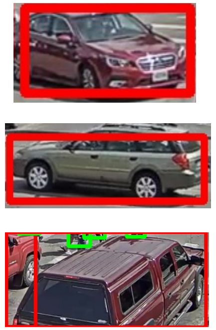


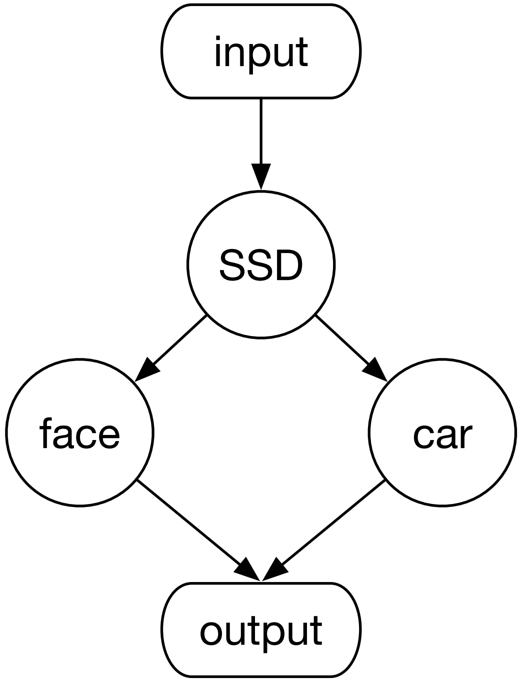
Case study: traffic monitoring



Persons

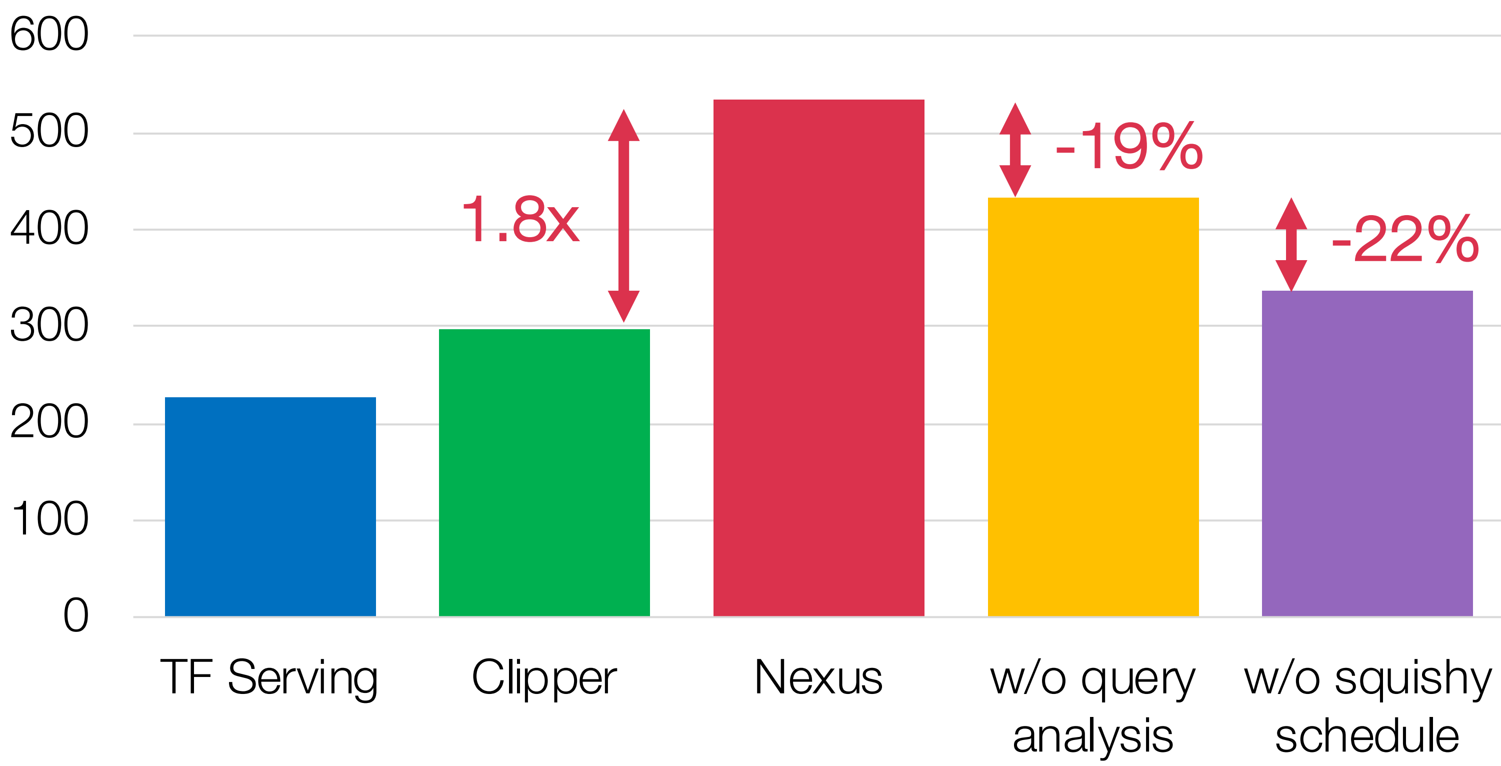


Cars



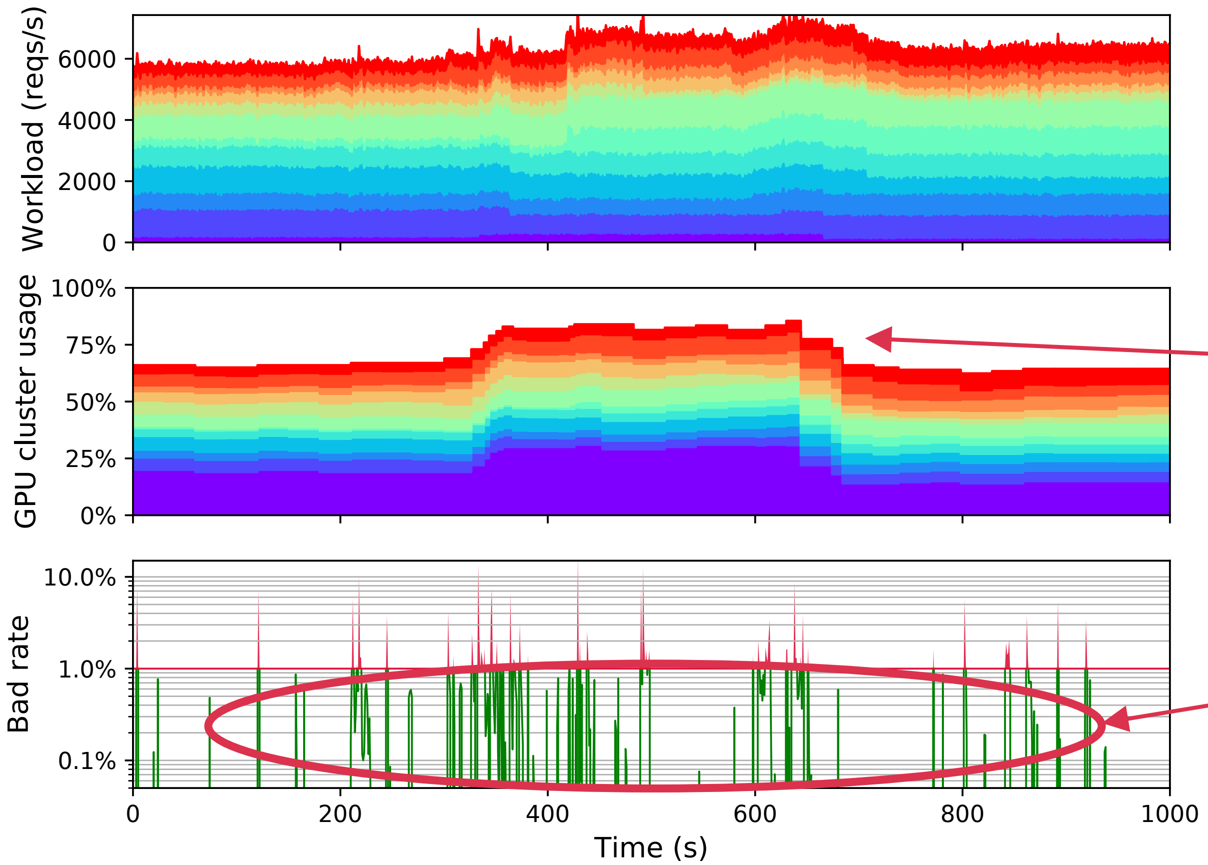
Case study: traffic monitoring

Latency SLO: 400ms, 16 Nvidia GTX 1080Ti



Large scale evaluation

- Deploy Nexus on 100 Nvidia K80 GPUs
- Run 7 different applications with changing workload



Adapt GPU allocation

Serve requests within latency SLOs

Conclusion

Nexus serves multiple applications at high utilization on a GPU cluster while satisfying latency SLOs

- Uses squishy bin-packing to schedule DNN workloads
- Analyzes complex queries
- Enables prefix batching across models

Code available at
https://github.com/uwsampl/nexus