Fast and Efficient Model Serving Using Multi-GPUs with Direct-Host-Access

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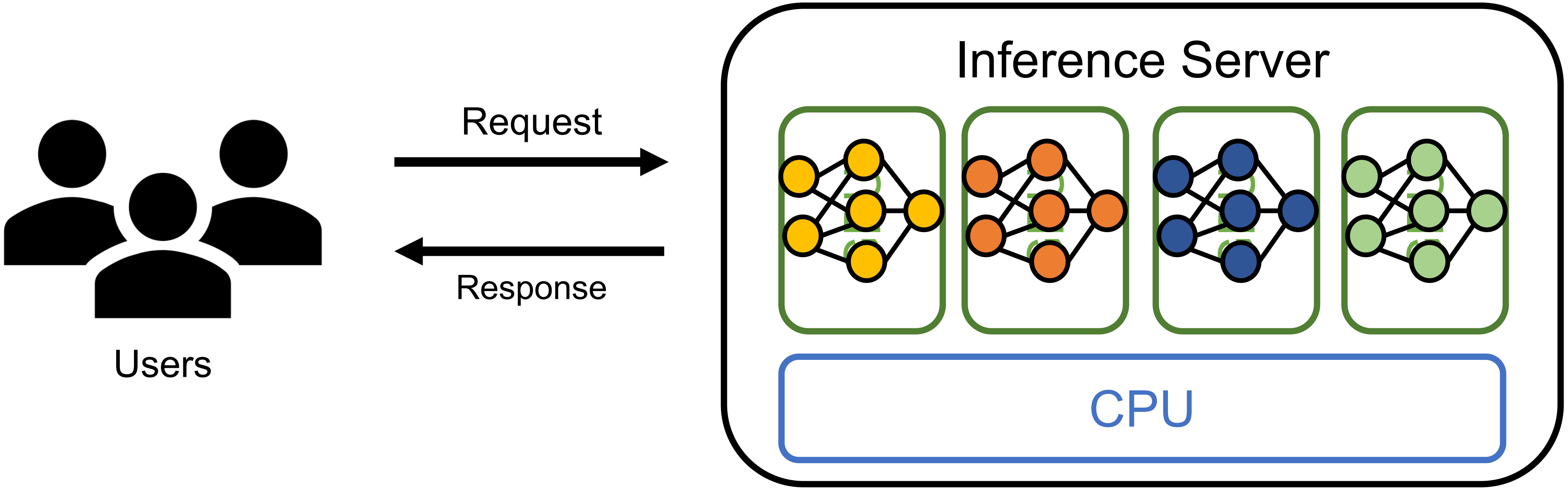
DL Model Serving Systems

- Important to serve incoming inference requests with low latency
- Existing inference serving systems
  - Keep DL models in GPU memory, enabling requests to be immediately served



Growing Number of DL Models

- Number of DL models is growing every year

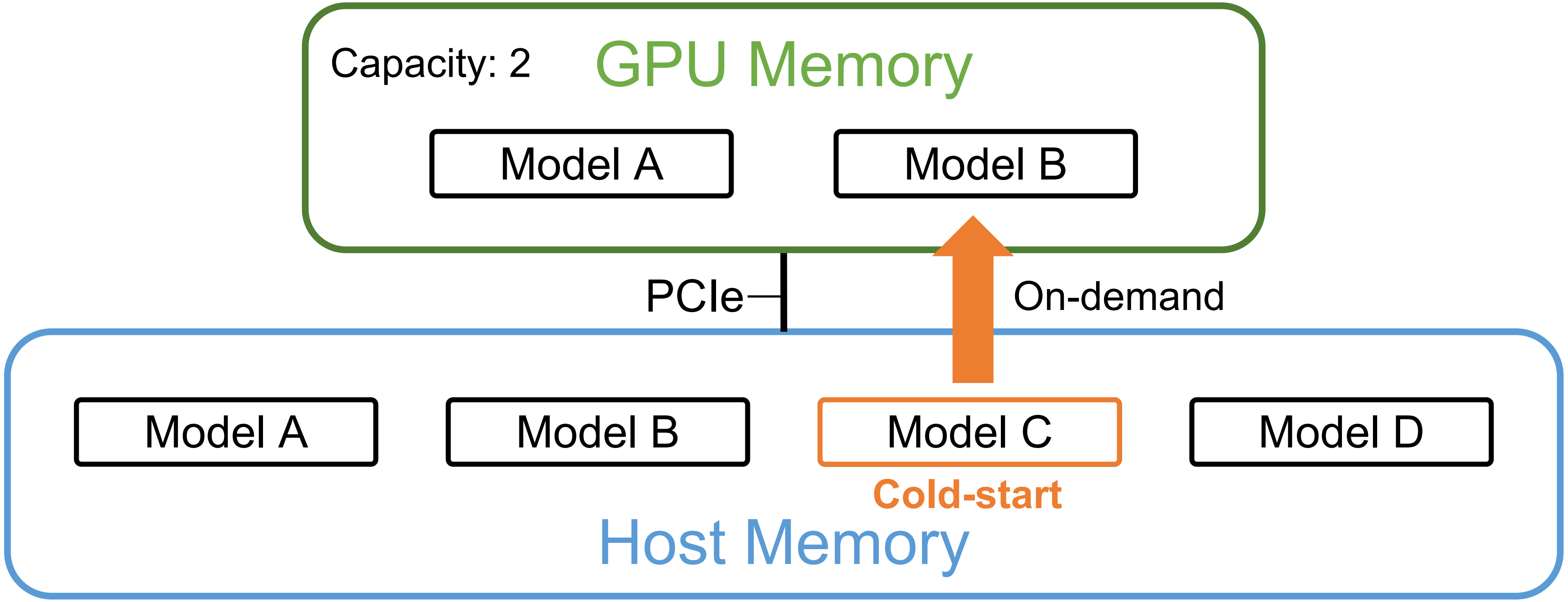
More number of models

Inference server provider's concern:

1. Limited GPU memory
2. Increasing the number of servers
3. Increasing the operating cost of servers

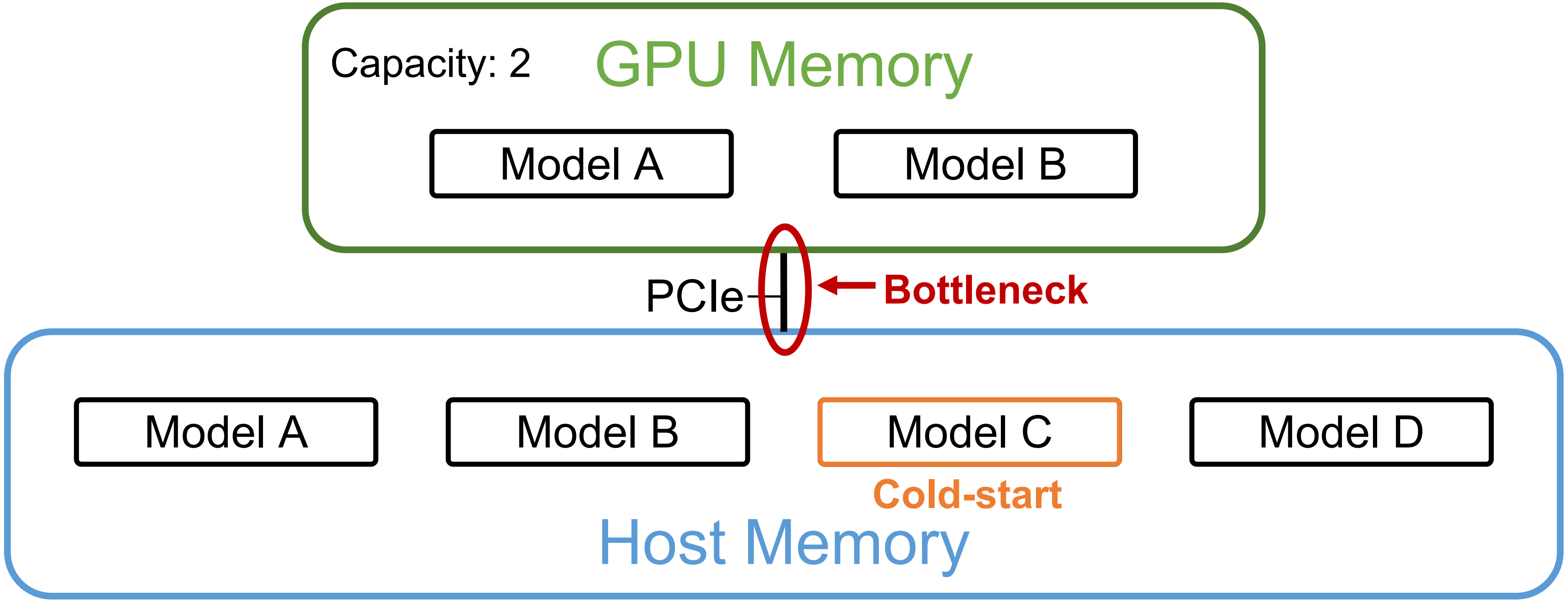
Leveraging Host Memory

- One promising approach to reduce the cost of GPU servers
  - Extend the number of models beyond the GPU memory limit



Cold-Start Problem

- However, such the cold-start affects the quality of user experiences
  - Makes it difficult to serve inference request within the desired SLO



Cold-Start Problem

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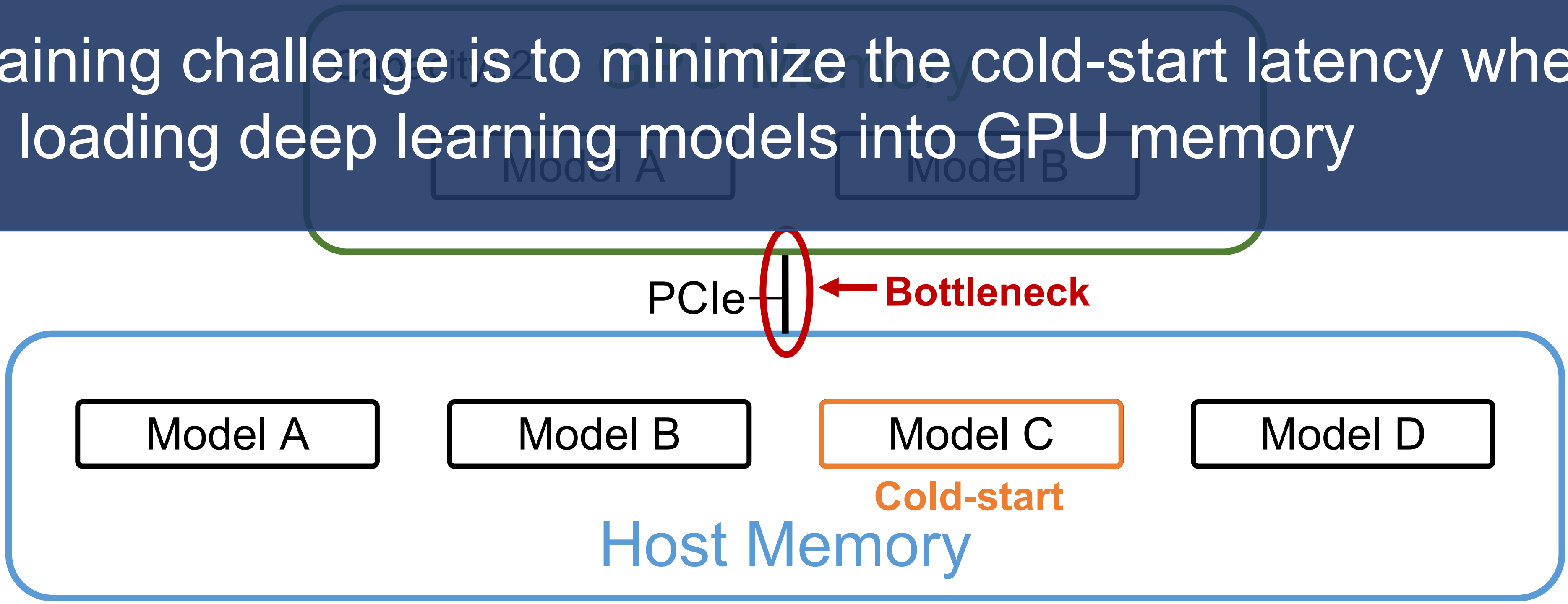
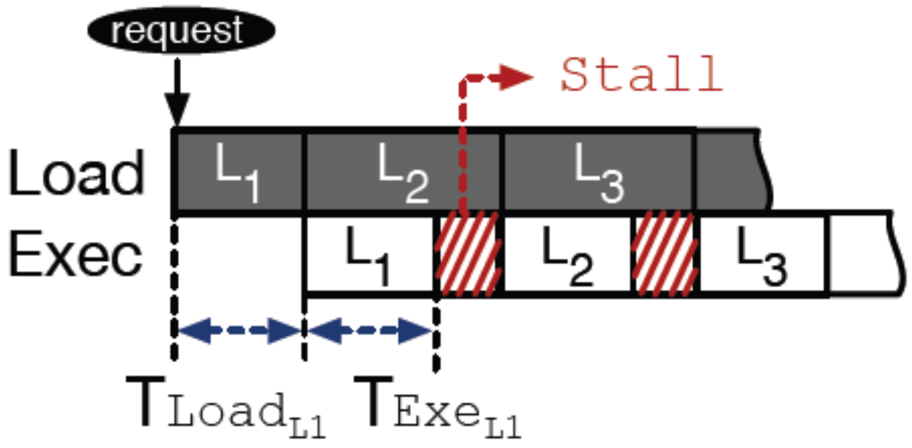
The remaining challenge is to minimize the cold-start latency when loading deep learning models into GPU memory

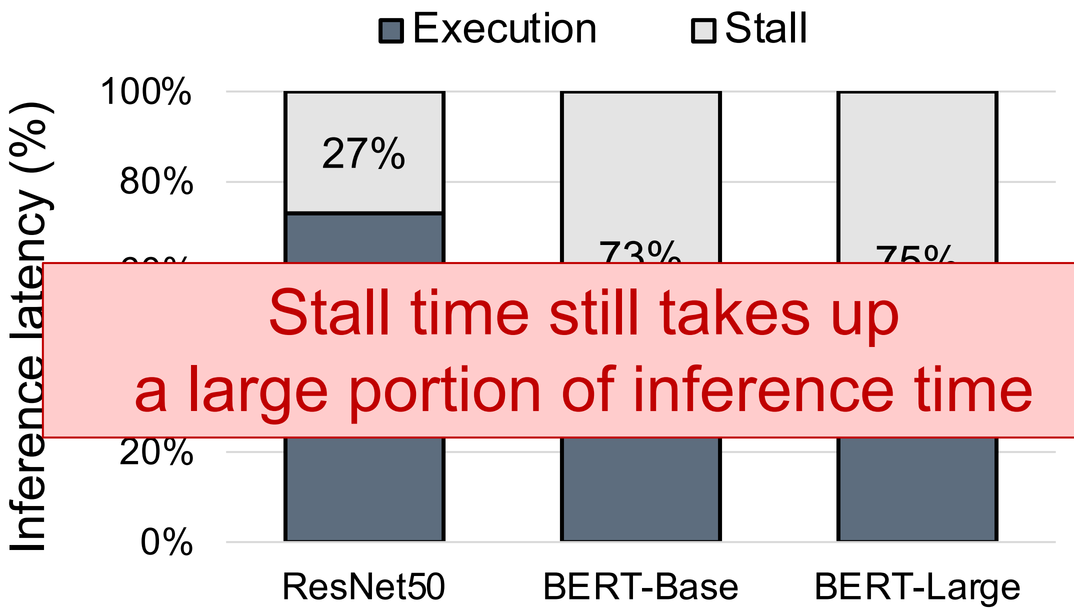


Pipelining Approach (Bai et al. OSDI'20)

- Pipeline the loading and execution of each layer
- Execute a layer as long as it is prepared in the GPU



Pipeline Approach



Stall time still takes up
a large portion of inference time

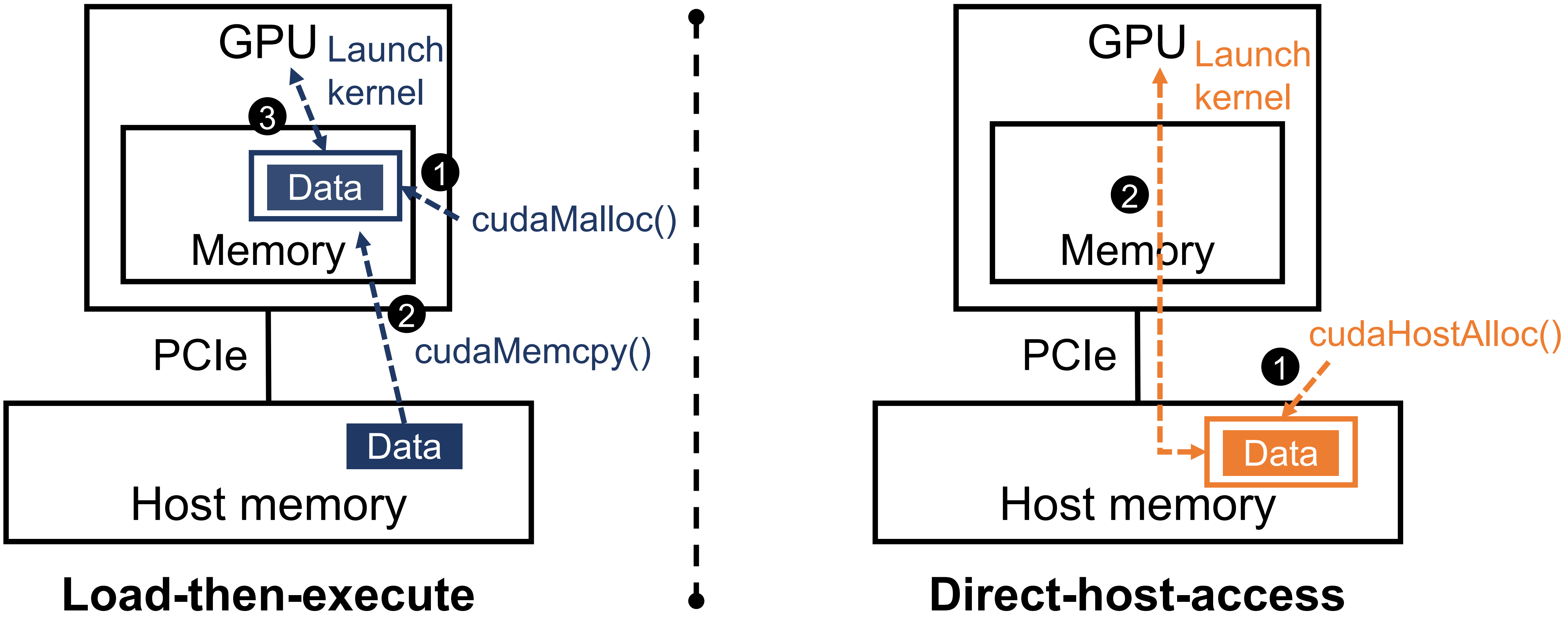
Our work focused on reducing the stall time

* Z. Bai et al. Pipelined Context Switching for Deep Learning Applications (OSDI'20)

Our Approaches

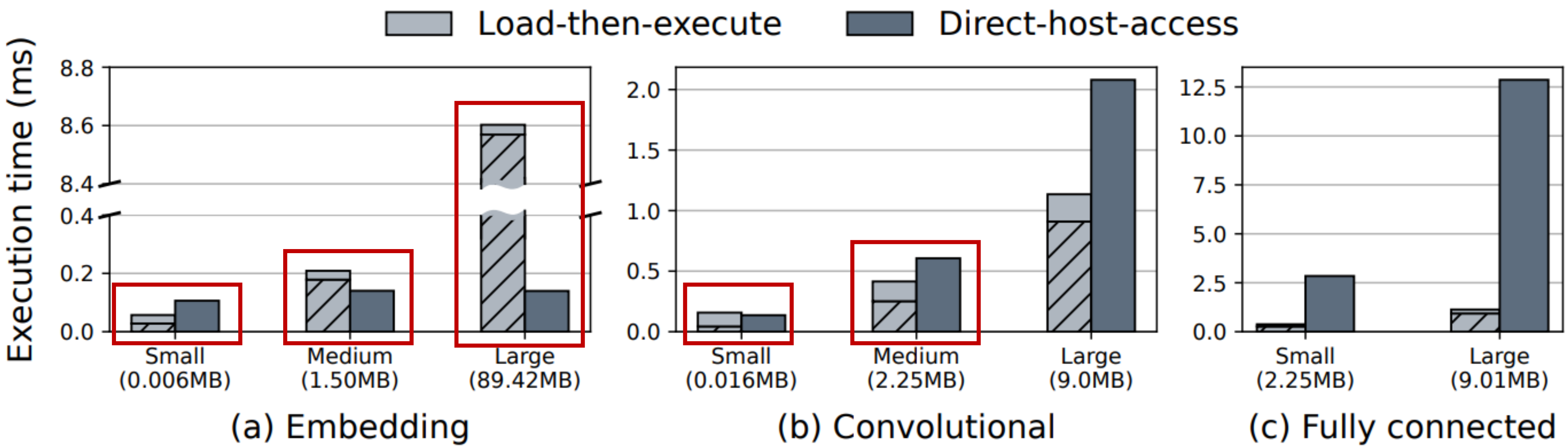
- Reducing the cold-start latency
  1. Leveraging direct-host-access
     - Applying direct-host-access to layers that can reduce stall time with direct-host-access
  2. Leveraging parallel model transmission
     - Further reduce stall time by using multi-GPUs when loading models
- Incorporating the above two approaches
  3. DeepPlan: automatically generating optimal inference execution plans

Two Methods for Computing on GPU



Performance Analysis for Direct-Host-Access

- We analyzed the performance for layers used in popular DL models



Apply DHA to layers which have performance benefits

Embedding: BERT-Base, Convolution: ResNet50, Fully Connected: BERT-Base

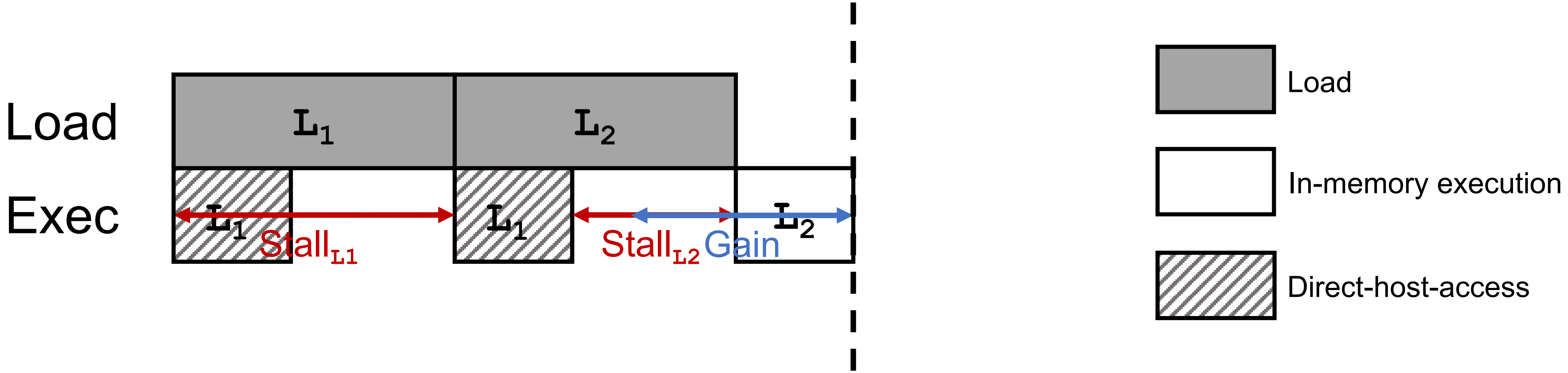
Advantages of Direct-Host-Access

1. DHA doesn't need to reserve the GPU memory
   $\Rightarrow$ DL model can be served with less memory usage
   $\Rightarrow$ Keep more models in GPU memory

2. While GPU executes a layer using direct-host-access, it can simultaneously load other layers
   $\Rightarrow$ Reduce or even eliminate pipeline stall
   $\Rightarrow$ Speed up model execution

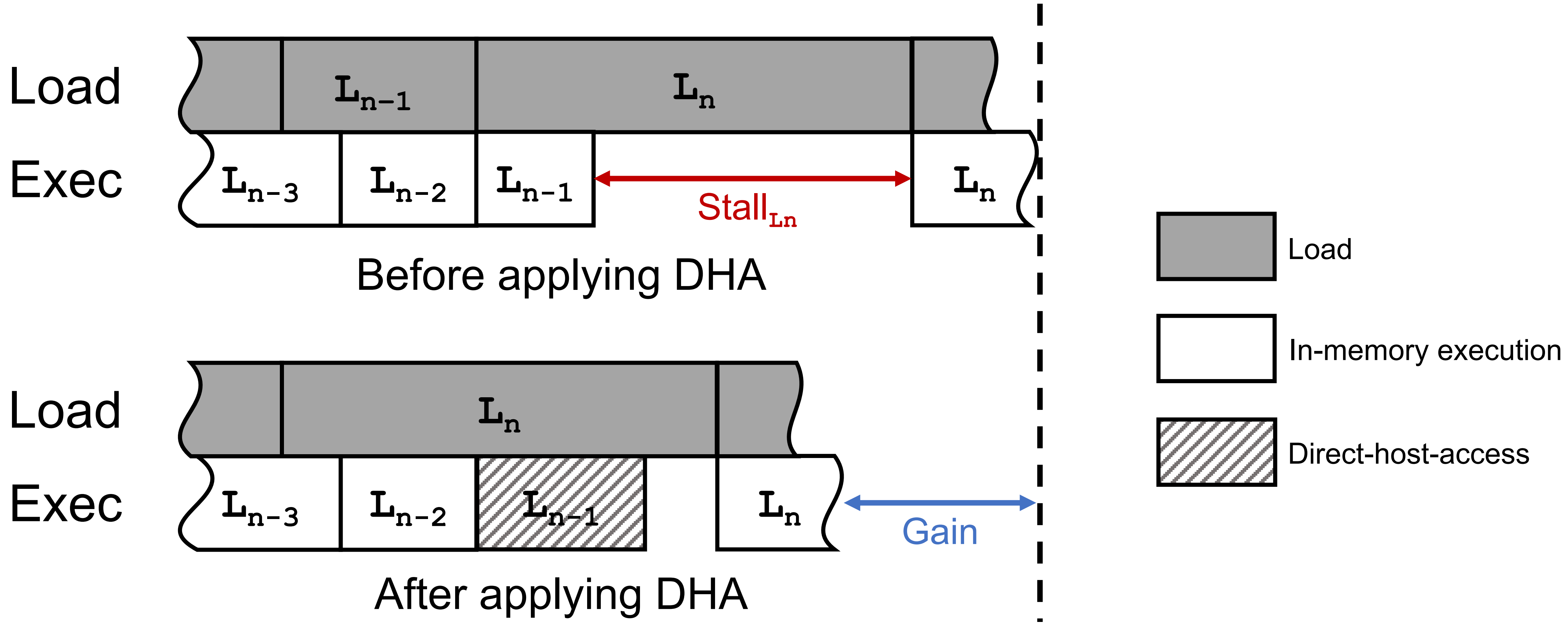
Leveraging Direct-Host-Access

- Acceleration of $\mathtt{L_1}$ execution
  1. Replace the $\mathtt{L_1}$ layer with direct-host-access
  2. Advance the loading of the $\mathtt{L_2}$ layer and the execution of the $\mathtt{L_1}$ layer
  3. The $\mathtt{L_2}$ layer can start earlier than with the simple pipeline approach



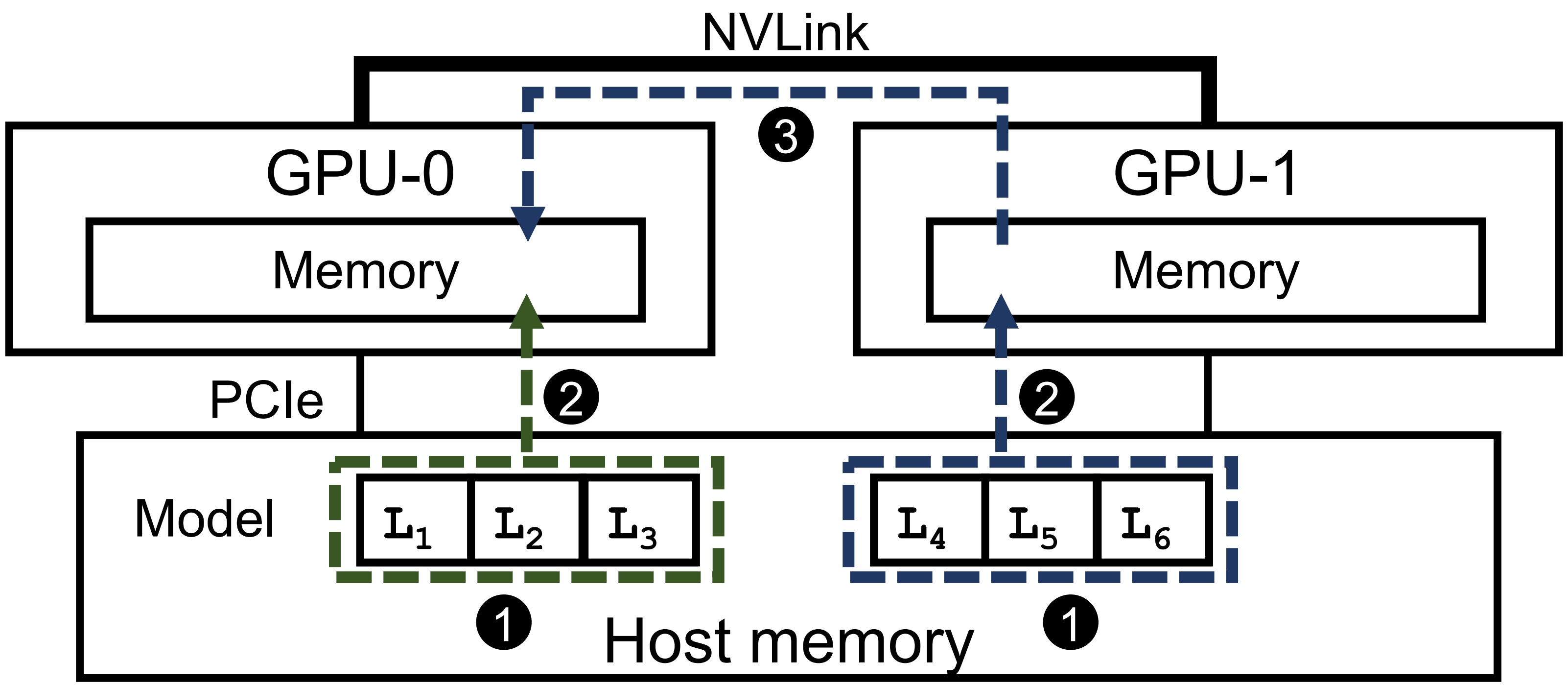
Leveraging Direct-Host-Access

- Reduce stall time of the L_n layer



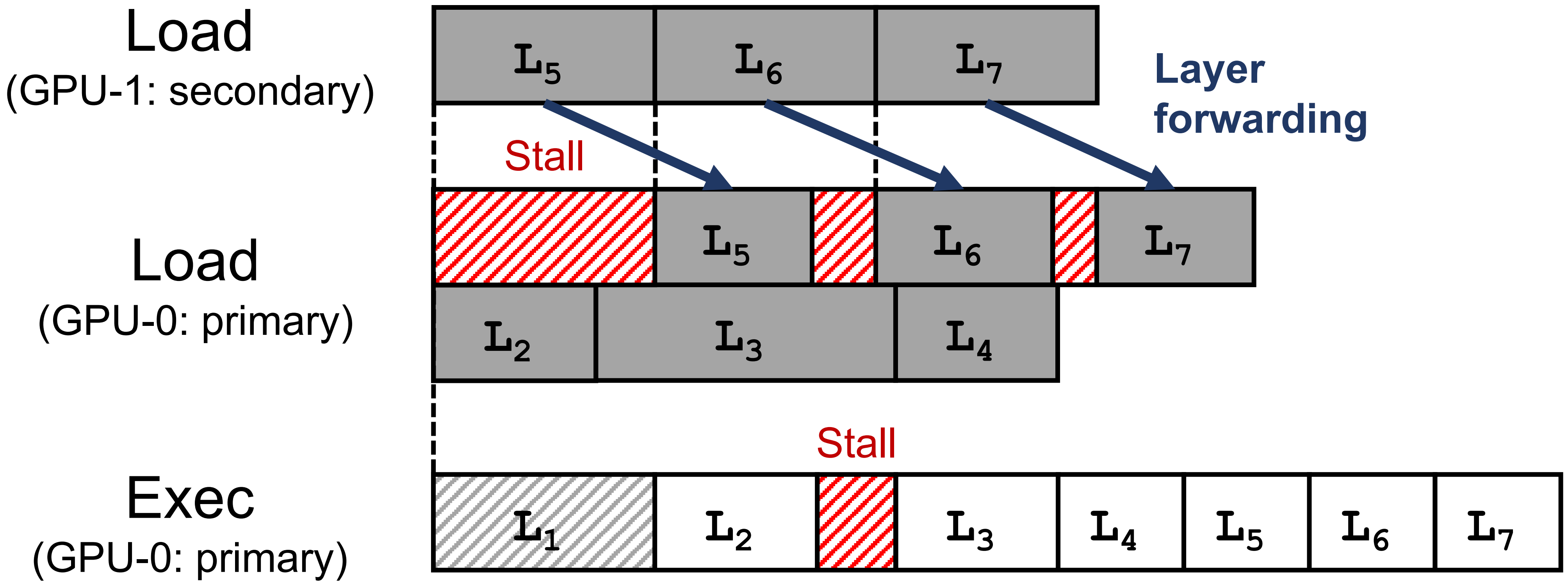
Parallel-Transmission (PT)

- Utilize multi-PCIe lanes to load a single DL model
  1. Divide the DL model into two partitions
  2. Distribute the partitions across two GPUs
  3. Merge the partitions into the GPU that has the first partition



Leveraging Parallel-Transmission

- Cooperative parallel-transmission with direct-host-access to accelerate model provisioning



Challenges

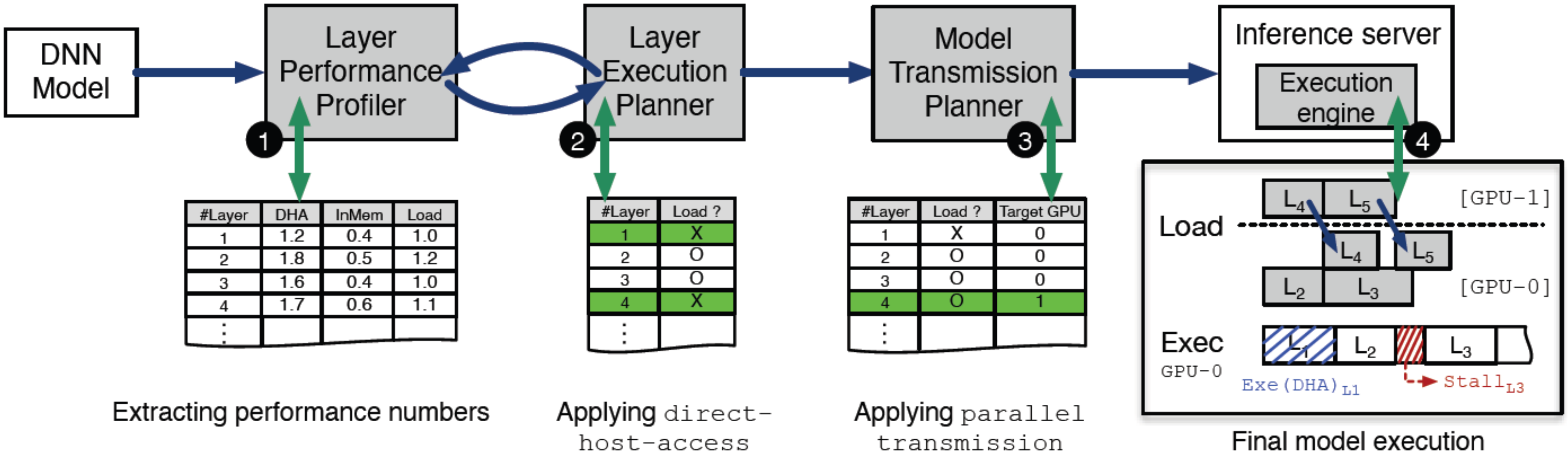
- Modern DL models and GPU servers are becoming diverse and complex
  - DL models have too many layers
  - A wide variety of server environments
    - Number of GPUs, GPU type, Interconnect, etc.

- Applying DHA and PT manually to the layers of models is challenging

- **An automatic system could be needed to address these challenges**

DeepPlan

- Automatically generating an optimal inference execution plan for a given server environment and model



Experimental Setup

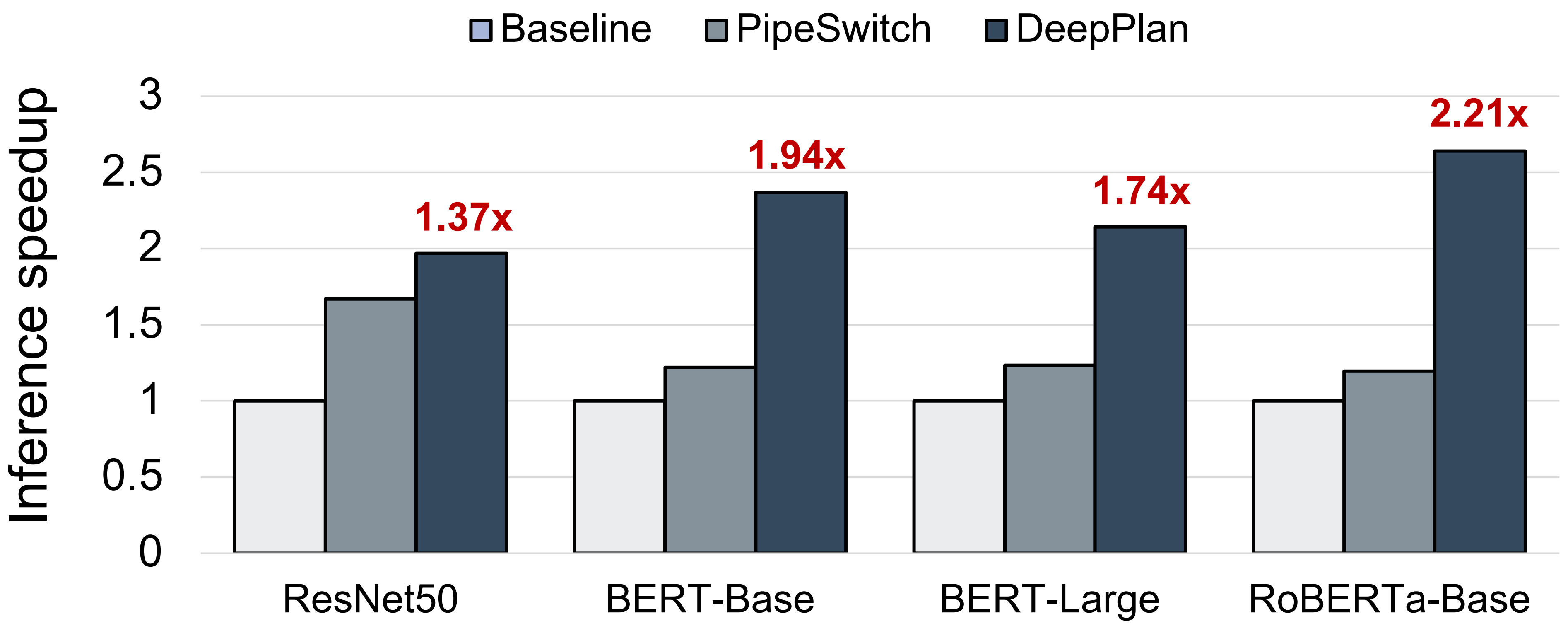
Hardware Setup	Four V100 GPUs with NVLink (AWS p3.8xlarge instances)	
Comparison	Non-pipeline (Baseline), PipeSwitch* (OSDI'20), DeepPlan (Ours)	
Framework	LibTorch v1.9.1 (PyTorch C++)	
Workloads	Vision models	ResNet50, ResNet101
	NLP models	BERT, RoBERTa

Source code: https://github.com/csl-ajou/DeepPlan

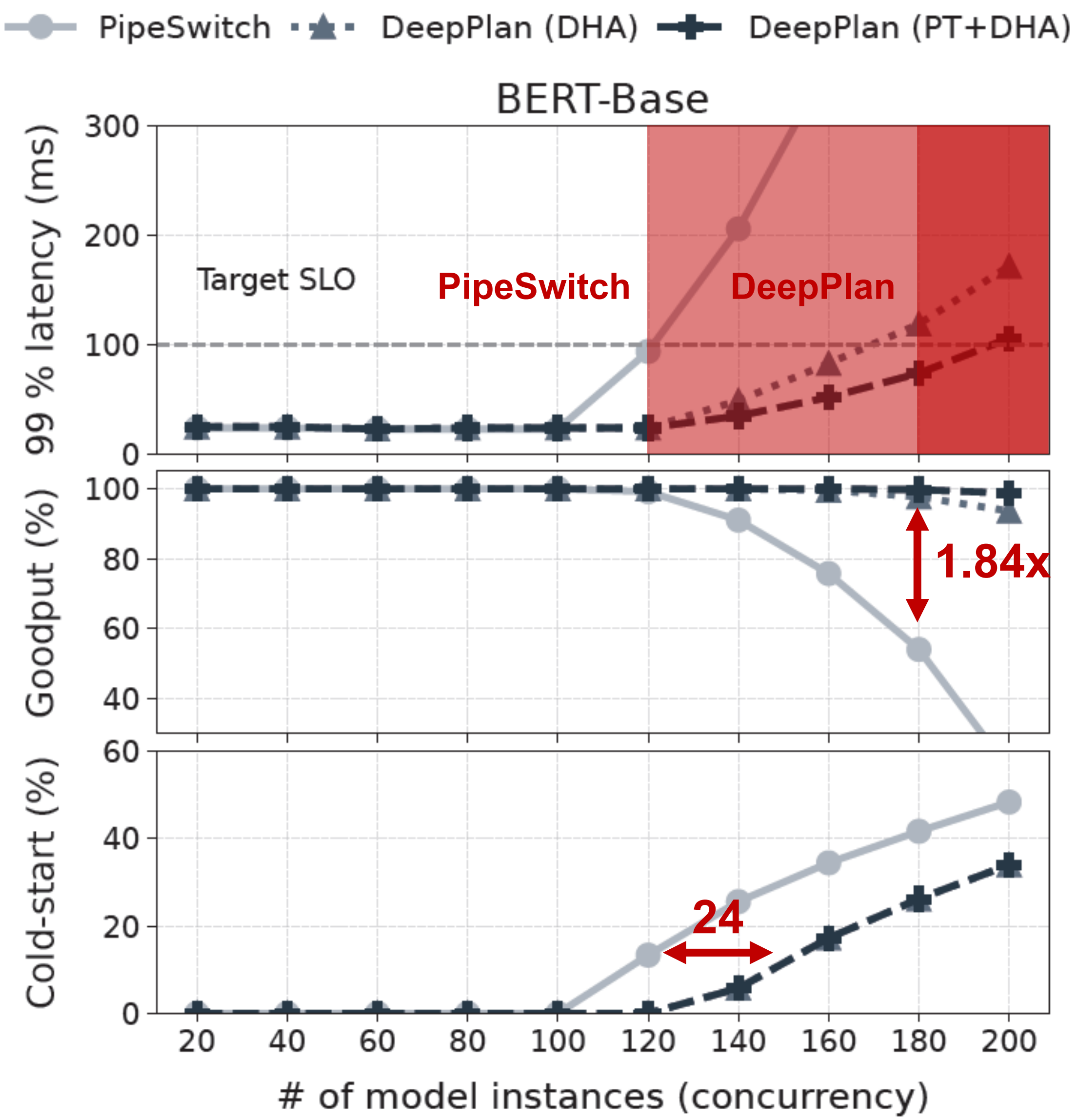
* Z. Bai et al. Pipelined Context Switching for Deep Learning Applications (OSDI'20)

Single Inference with Batch Size 1

- DeepPlan outperforms PipeSwitch across all models

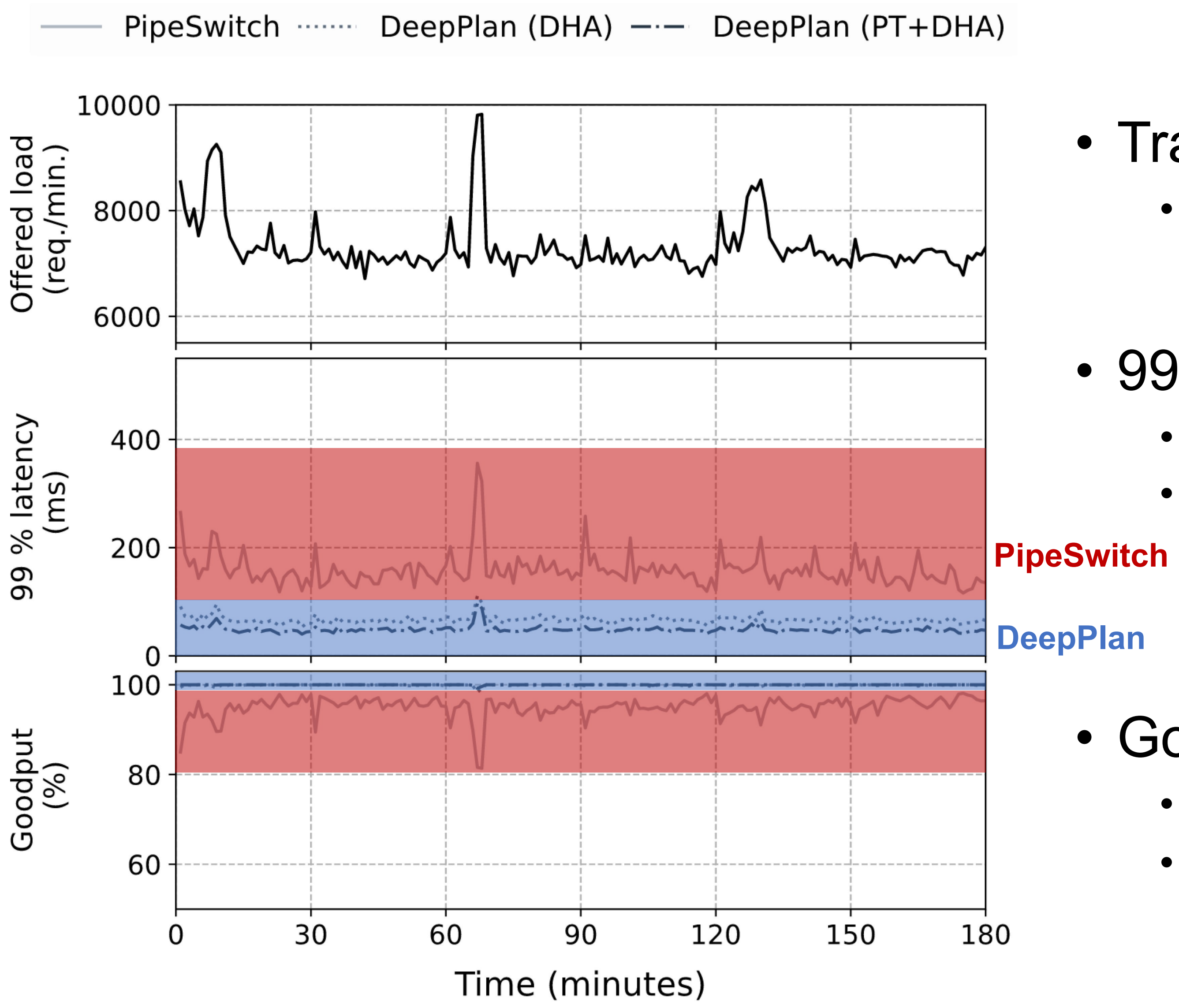


Increasing the Number of Models



- 99% latency, goodput, and cold-start
  - Used Poisson distribution
  - Target SLO: 100ms
- Maximum number of instances without violating SLO
  - PipeSwitch: 120
  - DeepPlan: 180
- Goodput at 180 concurrency
  - Improved by 1.84x compared to PipeSwitch
- GPU memory space required for models
  - DeepPlan keeps 24 more instances

Real-World Workloads (3 hours)



- Trace of Microsoft Azure Functions
  - Heavy sustained requests, fluctuations and spikes
- 99% latency
  - DeepPlan: 100ms ↓
  - PipeSwitch: 150ms ↑
- Goodput
  - DeepPlan: 98% ~ 99%
  - PipeSwitch: 81% ~ 98%

Conclusion

- Cold-start affects the quality of user experiences
- We exploited DHA and PT for minimizing cold-start latency
- We built DeepPlan for automatically generating inference execution plans
- DeepPlan could significantly reduce the stall time and improve the performance of serving inferences

Thank You!

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