Spatial Sharing of GPU for Autotuning DNN models

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Abstract

GPUs are used for training, inference, and tuning the machine learning models. However, Deep Neural Network (DNN) models vary widely in their ability to exploit the full power of high-performance GPUs. Spatial sharing of GPU enables multiplexing several applications on the GPU and can improve utilization of the GPU, thus improving throughput and lowering latency. DNN models given just the right amount of GPU resources can still provide low inference latency, just as much as dedicating all of the GPU for their inference task. An approach to improve DNN inference performance is hardware-specific tuning of the DNN model. Autotuning frameworks find the optimal low-level implementation for a certain target device based on the trained machine learning model, thus reducing the DNN’s inference latency and increasing inference throughput. We observe an inter-dependency between the tuned model and its inference latency. A DNN model tuned with specific GPU resources provides the best inference latency when inferred with close to the same amount of GPU resources. However, a model tuned with the maximum amount of the GPU’s resources has poorer inference latency once the GPU resources are limited for inference. On the other hand, a model tuned with an appropriate amount of GPU resources still achieves good inference latency across a wide range of GPU resource availability. We explore the underlying causes that impact the tuning of a model at different amounts of GPU resources. We present a number of techniques to maximize resource utilization and improve tuning performance. We enable controlled spatial sharing of GPU to multiplex several tuning applications on the GPU. We scale the tuning server instances and shard the tuning model across multiple client instances for concurrent tuning of different operators of a model, achieving better GPU multiplexing. With our improvements, we decrease DNN autotuning time by up to 75% and increase throughput by a factor of 5.

1 Introduction

Deep Learning (DL) powered inference use cases (e.g., industrial monitoring, autonomous driving) increasingly common. The high cost of performing the inference (both in hardware cost and power consumption) makes it critical to optimize the inference performance and as well to improve the user’s Quality of Experience (QoE). For example, Facebook needs to serve tens of trillions of inference requests in real time, which demands enormous amount of compute servers [9]. Thus,
there is significant demand for low-latency, high throughput, but still at high accuracy. Deep Neural Network (DNN) models for inference services. Several methods have been proposed to increase the accuracy and to speedup the DNN inference \cite{16, 7, 13}. GPUs are typically utilized to provide the necessary acceleration to achieve low-latency inference. Another complementary activity is to tune the DNN model to run efficiently on a specific hardware platform that the inference will be executed on, to find an optimal model configuration that can best utilize the hardware towards achieving very low-latency inference. Despite these efforts, tuned DNN models that are available today fail to utilize the power of current GPUs efficiently \cite{12}. GPU utilization by a DNN is further limited by several other factors such as data transfer to the GPU \cite{8}, memory access, irregular computation \cite{10}, etc.

We have also observed that some DNNs have lower GPU utilization due to the smaller computation need for some of their layers.

The objective of our work is two-fold: i) to provide optimally tuned DNN models for low-latency inference; and ii) to improve the tuning efficiency (increasing tuning throughput by reducing tuning time and multiplexing tuning instances) and GPU utilization. Towards this goal, we design mechanisms to effectively multiplex and concurrently execute multiple inference applications on a GPU. We leverage NVIDIA Multi-Process Service (MPS) and extend it by providing an appropriate amount of GPU resources (a GPU%, i.e., restricting the GPU resources provided for inference and for the tuning service by specifying the number of GPU Streaming Multiprocessors (SMs) that an application can use) to the DNN models to achieve low latency inference, while effectively freeing up the GPU to support running more tuning or inference applications concurrently. Therefore, multiplexing several applications on a GPU by spatially sharing the GPU can greatly increase its utilization.

We specifically explore the impact of tuning a model with constrained GPU resources (i.e., when the model is tuned with a specified GPU%), on its inference latency when the inference is performed with different GPU resource limits. As a motivating example we tuned a ResNet-18 model in TVM twice, once by setting GPU% to 100 and also by setting it to 25. We see in Fig. \ref{fig:1} that tuning a model with the maximum amount of GPU resources (100% GPU) provides a tuned model that works best only when most or entire GPU is dedicated for inference. However, that same model performs worse than a model tuned with a lower GPU% when both perform inference with fewer GPU resources (e.g., 25% GPU or less). In fact, a model tuned at ‘just the right’ GPU percentage performs better for a wider range of GPU% during inference. On the other hand, a model tuned at the extremes (too much or too little GPU resource) performs poorly during inference with a GPU% not matched to that extreme tuning. We present our observations about inter-dependency between a model tuned at a particular GPU% and its corresponding inference latency in \S \ref{ss:var} and experimentally examine and illustrate the reasons for such inter-dependency. Further, we devise techniques to spatially share the GPU to decrease tuning latency and increase tuning throughput.

2 Background

2.1 DNN Autotuning Systems

*Autotuning* or the automated performance optimization of DNN models creates optimized low-level implementations of DNN operators (e.g., 2D convolution, fully connected layers, pooling) for a specific target hardware (e.g., GPU, FPGA, CPU, etc) to improve inference performance without the need for manual tuning human experts. Specifically, autotuning finds optimal configurations for loop tiles and ordering, caching, and loop unrolling to reduce the memory access cost, maximize parallelism (e.g., CUDA threading), and leverage novel hardware primitives (e.g., Tensor Cores) wherever possible in the target hardware. The high-level procedure of autotuning is to have a large number of iterations of sequential evaluations of different DNN model configurations before finding an optimal one. Fig. \ref{fig:1} shows a generic autotuning procedure to optimize inference performance on target devices. It consists of four stages: (1) Select configurations: selects a batch of candidate configurations in a search space based on the Search strategy stage. In case no initial training data exists, this stage picks random candidate configurations. (2) Build: generates executable files based
We refer the quality of tuned model in terms of the inference time achieved by the tuned model when executed with 100% GPU and also evaluate the quality based on the variance a model shows in the inference time when executed with different GPU%. To measure the impact on inference time we perform inference using the tuned models (tuned at different GPU%) by explicitly limiting the GPU% during the inference operation. For this evaluation we allowed the model to be tuned until the early stop option in TVM terminates the tuning. With early stop, TVM’s schedule explorer checks,

on this batch of candidates. (3) **Profile:** runs executable files and measures the execution time on the target device(s). Note that the autotuning procedure has to run on a specific target device that we want to optimize the model for. (4) **Search strategy:** selects the next promising candidates in a search space and consists of an exploration algorithm and a Machine Learning (ML) cost model. The exploration algorithm (e.g., simulated annealing [14], and reinforcement learning-based search [2,3]) is used to reduce the search space to select the next configurations in the search space with the ML cost model (e.g., XGBoost [4], Graph Neural Network [19]). Since every iteration has the order of billions of possible configurations, it is very important to reduce the search space to make it possible to use in real world DL workloads. The ML cost model is trained based on selected configurations and their corresponding execution times measured in the **Profile** stage and used to predict the execution times of configurations in the exploration algorithm without hardware measurements. The Builder in fig. [1a] performs stages 1, 2, and 4, and Runner does stage 3.

**TVM AutoTuning System** is a popular DNN autotuning application [5] whose architecture facilitates tuning DNNs across multiple compute nodes (Fig. [1a]).

**TVM RPC Client** functions as the **Builder** process of the generic platform. It has: i) Schedule Explorer, searches for and proposes new configurations that provide more optimal DNN operators. The proposed configurations are first compiled by the target compiler (e.g., NVCC for NVIDIA GPUs), and then transferred to the TVM RPC server for profiling; ii) Cost Model, for reducing the search space and overall tuning time. TVM also has an early stopping module that halts tuning if a newer configuration generated by the explorer is worse than previously profiled configurations. **TVM RPC Server** is the generic **Runner** process running on the server compute node with the target hardware (e.g., GPU). It gets the compiled code from the TVM RPC Client, executes them on the target hardware and reports the result back to the TVM RPC client; **TVM Tracker** acts as a broker that coordinates and arbitrates the tuning process between the TVM RPC client and server components and additionally provides authentication and other security measures necessary to restrict/control the client-server interaction.

### 2.2 Impact of spatially sharing GPU with fixed percentage on tuning and inference

Effectively utilizing the GPU by multiplexing tasks running concurrently is challenging. The default NVIDIA GPU runtime environment executes one application at a time, even if there are enough GPU resources to allow multiple tasks. Applications share the GPU temporally by executing their GPU kernels in a fixed time quantum provided by GPU scheduler. This unfortunately increases the overall latency for all concurrently running applications. The CUDA Multi-Process System (MPS) [1] has been introduced to make concurrent execution of applications possible by spatially sharing the GPU to reduce idling of GPU resources. But, with default CUDA MPS, a compute heavy application can impact resources for other applications running concurrently, thus leading to unpredictable latency for other applications. Thus, we need to enhance the default CUDA MPS to share the GPU judiciously. The Volta (and newer) generation of NVIDIA GPUs provide a mechanism to set a limit on the amount of GPU resource for each running application by providing a GPU% as an environmental variable. This fixed GPU% approach helps us to isolate the GPU resources for a particular application and avoid interference from other applications, thus, guaranteeing predictable latency. TVM fundamentally requires that the profiling server reports the correct time taken by a configuration to execute in the GPU. Therefore, we design a mechanism to share the GPU spatially with fixed GPU%, while seeking to maximize the GPU utilization. We avoid interference that can occur while sharing the GPU, as seen with temporal sharing or using the default MPS. We discuss the effect of interference in the GPU has on TVM tuning in greater detail in the Appendix.

We now analyze the impact of tuning a model with one or more TVM servers spatially sharing the GPU using CUDA MPS that is setup to use different fixed GPU% and its impact on inference latency. We also study this interaction across multiple different DNN models. We note that although a DNN tuned at different GPU% has a different inference latency, the output of the inference remains the same. i.e., accuracy of the resulting tuned model is not affected.

#### 2.2.1 Impact on Inference time (Quality of tuned model)

We refer the quality of tuned model in terms of the inference time achieved by the tuned model when executed with 100% GPU and also evaluate the quality based on the variance a model shows in the inference time when executed with different GPU%. To measure the impact on inference time we perform inference using the tuned models (tuned at different GPU%) by explicitly limiting the GPU% during the inference operation. For this evaluation we allowed the model to be tuned until the **early stop** option in TVM terminates the tuning. With **early stop**, TVM’s schedule explorer checks,
and stops tuning, when the new configurations of the convolution operator do not show latency improvement. We use a sample color image of resolution 224×224 pixels to perform inference on. The results are shown in Table 1 and Table 2. Observe that for all the models, the inference latency is lowest when the GPU% set for inference matches the GPU% used while tuning (i.e., along the diagonal of the tables). We further observe that for the computationally lighter models such as ResNet-18 and Mobilenet, the models tuned at a higher GPU% have a relatively larger inference latency when inferred with a lower GPU% than what it was tuned at. e.g., A model tuned at 100% is optimal only when the inference task has 100% of the GPU, while it has a higher latency when inferred at lower GPU percentages. We see this pattern is consistent for both Table 1 and Table 2. A ResNet-18 model tuned (Table 1(left)) at 100% has 24% higher latency than the same model tuned at 25% GPU, when both are inferring with 10% GPU. However, a model tuned at 100% GPU is only 9% faster than a model tuned at 25% GPU, when both are inferred at 100% GPU. This indicates that there is a "sweet-spot" of GPU% for tuning a model such that the tuned model provides near-optimal latency over wider range of GPU% during inference. However, for computationally denser models such as VGG-19, we do not see as much variation in inference latency (see Table 2 for VGG-19). To find the "sweet-spot" we ran an experiment where we take DNN models tuned at different percentages and infer 1000 images (with batch size of 1) each at GPU% of 10,25,50,75 and 100 and compute the total time taken to infer all 5000 images. We see that for Mobilenet, ResNet-18 and VGG-19, models tuned at 25% provide the best inference times for 5K images.

Table 1: ResNet-18 & Mobilenet Inference Latency (ms): tuning and inference at different GPU%

| Inference% | Tuning% (ResNet-18) | 10 | 25 | 50 | 75 | 100 | Untuned |
|------------|---------------------|----|----|----|----|-----|---------|
| 10         | 3.13                | 3.53 | 4.03 | 4.32 | 4.38 | 13.18 |         |
| 25         | 2.06                | 1.83 | 2.03 | 2.10 | 2.18 | 5.54  |         |
| 50         | 1.75                | 1.41 | 1.34 | 1.43 | 1.42 | 3.06  |         |
| 75         | 1.71                | 1.27 | 1.21 | 1.17 | 1.22 | 2.24  |         |
| 100        | 1.64                | 1.22 | 1.17 | 1.11 | 1.10 | 1.87  |         |

Table 2: VGG-19 Inference Latency (ms)

| Inference% | Tuning% (VGG-19) |
|------------|------------------|
| 10         | 3.09             |
| 25         | 2.78             |
| 50         | 2.64             |
| 75         | 2.51             |
| 100        | 2.41             |

We used the NVIDIA nvprof profiler to profile the tuned models and noted the number of GPU threads each model uses while inferring. This thread count is in Fig. 2. We can see that TVM’s tuning picks the configuration with a high thread count for a model tuned at 75% and 100% GPU. In an ideal scenario, more threads running concurrently can parallelize the work better, thus achieving lower inference latency. However, in a typical GPU only a fixed number of threads (e.g., for V100 GPU, only 2048 GPU threads) can be run in an SM concurrently. While thread count alone does not determine how the SMs in the GPU will be utilized, using more threads does indicate that more SMs are necessary to run those threads concurrently. Thus, if the model with a high thread count is run at lower GPU%, there will not be enough SMs to run the threads, and hence each operation will take longer to complete.

Figure 2: # of GPU threads in each convolution operation of Mobilenet tuned at different GPU%

Figure 3: Inference runtime with 25% GPU.

Table 4: Model tuning time (mins) different GPU%
To show the impact of having a large number of threads per convolution operations while inferring at low GPU%, we profiled the runtime of each convolution operation for Mobilenet models tuned at 100% and 50%, and then provided 25% GPU for inference. The results are in Figure 3. First, with the model tuned at 100% GPU, almost all the operators run slower than the model tuned at 50% GPU. This difference in the runtime is more significant in compute heavy non-depthwise operators (odd numbers in Fig. 3). As we noted, the thread count for all the convolution operators in Fig. 2 show that the model tuned at 100% GPU produces operators with a higher number of threads than when it is tuned at 50%. Operators with a higher thread count require more GPU resources to run all threads concurrently. Else, some threads have to wait for GPU SMs to free up, thus, increasing the runtime of the operator. Thus, a model tuned at 100% GPU may be at a disadvantage compared to model tuned at 50% GPU, when during inference only 25% GPU is available with fewer available threads.

Figure 4: # of GPU threads used in each ResNet-18 convolution operator (tuned at different GPU%)

We also evaluated tuning ResNet-18. We show thread count in Fig. 4 and note a similar trend as with Mobilenet. We should note that for some operators, such as 2, 5, 8 and 11, the thread count is very low. These are the convolutional operators used in “skip connections” in ResNet and are used to change the dimension of data “skipping” from one layer to another. As they only change the dimension of the matrix, they are relatively light in computation, have lower GFLOPS, and require fewer threads. The remaining convolution operators perform more computation and require a higher number of threads.

### 2.2.2 Impact on Tuning time

We profiled a number of DNN models in TVM to understand the impact of varying the GPU% on total tuning time. To have a fair comparison across different GPU%, we fixed the number of tuning iterations per DNN operator to 1000. We present the results in Table 4. Although the tuning time for a DNN model varies slightly across different GPU%, the differences are marginal. The overall impact on tuning time across all the profiled models is seen to be less than 3% (the highest variability is for VGG-19). Therefore, we conclude that we can tune a model at a lower GPU% without adversely affecting the model tuning time.

### 3 GPU Multiplexing Design

#### 3.1 Improving the Autotuning Performance and System Utilization

The default TVM implementation does not recommend using more than one TVM server per GPU device due to interference multiple servers can cause during profiling. The TVM server receives the configuration files, invokes the GPU for profiling each of the configurations and reports the results back to the client, which then runs an exploration algorithm (simulated annealing) and ML algorithm (XGBoost) to evaluate what configurations to create for profiling in the next iteration. Since the client-side processing is also reasonably complex, there is essentially a ping-pong of server-then-client processing for each set of configurations. This results in very high idle time on the TVM server (and hence the GPU). As shown in Fig. 5a, the server remains idle for more than 50% of the total tuning time, while waiting for the client to complete its processing. Furthermore, the GPU is idle for \(\sim 85\%\) of tuning time. This poor utilization of server resources results in very low tuning throughput for the system.

A common approach to improve utilization is to multiplex and concurrently profile multiple (same or different) models. For example, concurrently tuning two Resnet-18 models using a single TVM

\[\text{We define tuning throughput as the number of auto-tuning jobs that can be completed per 1000 minutes.}\]
server decreases the server idle time from 50\% to 13\% of the total tuning time. However, the overall tuning time of the models increased by about 20\% (i.e., from 465 minutes for a single instance to 555 minutes to tune two models of ResNet-18). TVM clients are bursty in nature while profiling configurations, i.e., they produce a large number of configurations and profile them at once. This bursty nature causes delay even though the server is still idle for only 13\% of the time. Nonetheless, the multiplexing approach significantly improves overall tuning throughput (∼ 40\% in this case).

**TVM Server Instance (TSI) Scaling:** Tuning (single or multiple models) with multiple TVM server instances on a single server node helps improve resource (CPU and GPU) utilization and also considerably improves overall tuning throughput. However, the cost of multiplexing in terms of the increase in overall tuning time and the side effect on the quality of tuned model and the subsequent impact on inference latency due to the sharing of server resources need to be carefully considered. We aim to reduce the overall tuning time and increase the GPU utilization by running multiple TSIs concurrently on distinct CPU cores of a multi-core server node in such a way that it does not adversely impact the quality of the tuned model and it does not substantially increase the inference latency. TSI scaling can shard a single model across TSI, with each server instance on a different CPU core on the system. This improves utilization of both CPU and GPU on the server. The net effect is increased tuning throughput and lower latency to tune a single model. Additionally, to improve GPU utilization and fully take advantage of the number of CPU cores with multiple TSI running concurrently, we can tune multiple models concurrently and improve overall tuning service throughput. Further, we have also observed (Table 3) that a model tuned with appropriate GPU\% (e.g., 25\% for Resnet-18) performs better inference for a wide range of GPU\%. Thus, we seek to autotune different DNN models with an appropriate GPU\%, which also improves GPU utilization.

### 3.1.1 Scaling auto-tuning performance

Techniques to improve auto-tuning performance, including those described in the previous subsection seek to effectively multiplex multiple TVM server instances (TSI) that profile tasks on the GPU. These techniques utilize spatial sharing of the GPU to provide lower latency and higher throughput while tuning. This spatial sharing provides controlled sharing of the GPU.

**Spatially sharing with explicit isolation of GPU across multiple TVM servers:** We launch multiple TSI on the same profiling server node and spatially share the GPU by assigning each TSI with a distinct GPU\%. e.g., Fig. 5c shows two TSIs with 50\% GPU each. Further, the TVM tracker balances the load from the TVM client equally among different TSIs. Hence, the workload of a single TSI is distributed across multiple TSIs and thus lowers the overall tuning time.

**Sharding a model across multiple TVM clients:** The TVM client (TC) creates new configurations of a DNN operator for profiling that are packaged and sent to the server for profiling. Based on the results obtained from profiling, the subsequent processing at the TC can be substantial (e.g., running simulated annealing [14] and XGBoost [4] for search strategy stage and compiling next batch of configuration for target GPU). Hence, the TC itself can be a bottleneck while tuning. Also, we observe from Fig. 5c that the TC processing has the least idle time. To improve the TC performance, we scale the TC instances (TCI) and shard the convolution operators of the tuning model across different TCIs (that may run on multiple CPU cores). This is based on the key insight that auto-tuning a DNN model typically involves tuning distinct layers; but these are often tuned independently and thus can be sharded across multiple TCI. When all the TCIs finish tuning their respective layers, we combine the tuning results to get a tuned model. We have verified that model tuned using sharding approach has much lower inference latency than an untuned model. The final tuned model also has same accuracy as the untuned model, therefore, does not suffer from accuracy loss due to sharding.

**System Optimization:** We also performed another key system optimization to improve the TVM tuning time. The default TVM servers fork a child process to carry out the profiling of a configuration. This necessitates every child process having to create a GPU context before profiling the configuration in the GPU. But, the GPU context creation takes about 300 milliseconds, which is a significant portion of average overall time to profile a single configuration (which is ∼1.5 sec). GPU context setup accounts for more than 95\% GPU utilization during tuning, while the actual configuration profiling time is very low as seen in Fig. 5c. During the initialization time, the TSI process cannot use the GPU to profile the configuration received from the client. Hence, to avoid the frequent GPU context creation cost, we use a long-lived server which does not fork every new profiling task. Instead, the long lived server profiles the received configuration by executing it as a function. Running a large number of configurations in a single long lived process eliminates significant amount of GPU initialization costs, helping to lower the overall model tuning latency.
4 Evaluation

We evaluate the benefits of our optimizations with the most recent version of the open-source TVM implementation (v0.7) running on a testbed of multicore servers equipped with GPUs in our laboratory. We use two identical Dell PowerEdge R720x servers, each with 512 GB of memory and CPU with 40 cores. Each server is equipped with 1 NVIDIA V100 GPU with 16 GB of memory and 80 Streaming Multiprocessors (SMs). Both servers are connected back-back with a 10GbE Ethernet link.

4.1 Benefits of TSI Scaling and Sharding the model across multiple TCIs

We evaluate the impact on autotuning completion time due to the scaling of TSIs and sharding of the model across multiple TCIs. For these evaluations, we autotuned the ResNet-18 and Mobilenet models in isolation with different TVM client and server instances as distinct experiments. We set the maximum number of tuning iteration to 1000.

Scaling of TSIs: For this experiment, we use a single TC. We start with 1 TSI and then scale to 2 and 4 TSIs. The results in Fig. 6a show that the tuning time decreases with increasing number of TSIs for both the models. For ResNet-18, scaling to 4 TSIs decreases the tuning time by 25% (from 465 minutes with single TSI to 349 minutes with 4 TSIs), while Mobilenet shows a 42% decrease (drops from 630 minutes for 1 TSI to 364 minutes with 4 TSIs).

Sharding the model across multiple TVM clients: For these experiments we shard the models across clients such that the tuning of convolution operators is distributed across multiple TCIs and each TCI uses a single TSI. Fig. 6b shows that sharding helps reduce the tuning time significantly. When compared to tuning a single model with one client, by increasing to 2 TCIs we improve the tuning time by about 48% for ResNet-18 (from 465 minutes to 210 minutes) and 43% for Mobilenet (from 630 minutes to 357 minutes) respectively. With four TCIs, the tuning time further improves from the single tuning instance by 75% (117 minutes) for ResNet-18 and 68% (198 minutes) for Mobilenet.

4.2 Increasing Tuning Throughput

We evaluated the tuning throughput achieved by our optimization of using multiple TVM profiling servers spatially sharing a GPU. We evaluated the scenario where we have a server node with 1, 2 and 4 profiling TSIs as we vary the number of TCIs (one node each per TCI). For this experiment we use multiple identical ResNet-18 models across all the client instances. We present the tuning throughput (models tuned per 1000 minutes) achieved in Figure 6c. Increasing the number of TCIs when there is only one TSI yields a limited increase in throughput, because the single CPU core becomes a limitation. However, with a larger number of TSIs on the server side, increasing the number of TCIs then results in significant throughput improvement. Adding new TCIs increases multiplexing, and thus the server utilization and throughput. TSIs are no longer underutilized or remain idle for long periods during the tuning process. Adding more TSIs and increasing the number of TCIs conflate the benefit by increasing multiplexing, reducing tuning time and a substantial increase in throughput.

4.3 Tuning Multiple Different DNN Models Concurrently

We now show how combining the scaling of the TSIs for a given model and concurrently having different TCIs for different DNN models can boost a tuning service’s throughput through effective multiplexing. We tuned a ResNet-18 and a Mobilenet model using 2 different TCIs, while increasing the number of TSIs from 1 to 4 and evaluated both overall throughput and individual model tuning time as shown in Table 5. Having only 1 TSI to concurrently tune the 2 models increases the latency of both models. ResNet-18’s tuning time increased by ~18% and Mobilenet’s by ~20% compared...
to the time taken to tune a single model in isolation. But, when we increase the number of TSIs to 2, both models finish tuning within 519 minutes (31% reduction from the single model in isolation tuning time), and with 4 TSIs, before 373 minutes, a 51% reduction. Thus, there is improvement for both models once we have an adequate number of TSIs. When tuning two different models, one may finish tuning earlier than the other, allowing the slower model to use the additional GPU resources to process, if possible. We conservatively estimate the improvement in throughput (models tuned in 1000 minutes) based on the time taken to finish tuning both models. Scaling the TSI from 1 to 4 increases essentially doubles the tuning throughput. Compared to separately tuning each model in isolation (throughput of 1.52 models per 1000 mins.), we can tune 2.68 models in the same time by concurrent tuning with an adequate number of TSIs.

We also look at the time spent on tuning each operator of Mobilenet (model taking longer to tune) in Fig. 7. After the ResNet-18 model completes tuning at around the 13th operator when using a single TSI (Top plot) and 12th operator when using 2 TSIs (bottom plot) the tuning process speeds up to match the tuning time for baseline Mobilenet. This is because Mobilenet’s tuning takes over the TSI and GPU resources freed up by the completion of ResNet-18 tuning.

### 4.3.1 Quality of Tuned Model

| 2 TCI   | ResNet-18 | Mobilenet | Throughput |
|---------|-----------|-----------|------------|
| # of Servers | Time (min.) | Time (min.) | (# tuned/1000 mins.) |
| Isolated | 465 | 630 | 1.31 |
| 1       | 552 | 761 | 1.92 |
| 2       | 420 | 519 | 2.68 |
| 4       | 340 | 373 | 2.68 |

Table 6: Long lived server tuning time (mins)

| # TSI | Default TVM | Long-Lived Server |
|-------|-------------|-------------------|
| 1     | 465         | 427               |
| 2     | 412         | 373               |
| 4     | 350         | 348               |

Table 7: Chameleon tuning time

We took the ResNet-18 and Mobilenet models tuned in §4.3 using 4 TSIs, each TSI using 25% GPU. We used those model for inference and profiled the inference with NVIDIA profiler to observe the GPU thread count each operator produces. We present the thread count in Fig. 8. We can see that most of the operators thread count do not exceed 50,000 mark. We see similar trend in Fig. 3 and Fig. 4 where the model tuned with 25% GPU also have most of their operators not exceeding 50,000 threads. Therefore, we see that multiple models tuned concurrently by spatially sharing the GPU produce similar model to one tuned in isolation.

### 4.4 Other System Benefits

**Long-lived Server:** We also evaluate the impact of having a long-lived server on tuning time of the model. We tune a ResNet-18 model using long-lived server, we further increase the number of TSIs. We present our result in Table 6. We can see that long-lived server helps to drastically reduce the unnecessary overhead on the GPU context creation time and thus reduce the overall tuning time.

**Chameleon Autotuning:** Likewise, we apply the optimization of scaling the TSI to the Chameleon [3] autotuning platform. We present the results in Table 7. We can observe that TSI scaling decreases the tuning time in Chameleon platform by ~20%. Note: The testbed used for this experiment is different and used a NVIDIA RTX 6000 GPU and 48 Cores CPU node. Hence, the default tuning time is different from the previous experiments we have shown.

### 5 Related Work

**Autotuning systems:** Recent works [18][5][20][15] propose deep learning compilers to improve the execution efficiency of neural networks (i.e., inference performance) on various hardware. In addition, extensive efforts [6][2][3][19] have been made to address performance problems (i.e., long autotuning completion time) in autotuning systems by enhancing exploration algorithms [6][2][3] and ML cost models [6][19]. Our work is complementary to those works, but differs from them in the sense that we propose a system to reduce autotuning time by multiplexing resources (e.g., GPU) for autotuning procedures and optimizing a profiling server (e.g., avoiding heavy CUDA initialization overhead).

**GPU sharing for ML Inference:** Recent works [11][17] have shown sharing GPU resources for inference help to improve GPU utilization. Our work differs from them. First, we focus on sharing GPU resources for autotuning procedures. Second, we studied GPU sharing impact on inference performance based on tuned models from the autotuning procedures.

### 6 Summary

In this paper, we make the case for controlled spatial sharing of GPU for tuning DNN models. We noted the inter-dependency between model tuning and inference with the tuned model with an appropriate GPU%. DNN models tuned with the appropriate GPU resources (GPU%) provide better models, having lower inference latency over a wider range of GPU%, than models tuned with 100%
GPU. We also show that tuning with a high GPU% results in a model that requires a large number of threads for each convolution operator, thus incurring additional latency during inference, especially when inference is done with less hardware resources (lower GPU%). Based on these observations, we recommend the DNN models to be tuned at an appropriate GPU% (several models we tuned needed no more than 25% GPU) instead of 100%, which also allows for better multiplexing and utilize the remaining GPU resources to tune other DNN models. We present the mechanisms namely, TSI scaling, TCI sharding the model and having a long-lived server process that reduce tuning time by up to 75% and achieve up to 5-fold increase in tuning throughput.

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