Unlike traditional resources such as CPU or the network, modern GPUs do not natively support fine-grained sharing primitives. Consequently, implementing common policies such as time sharing and preemption are expensive. Worse, when a deep learning (DL) application cannot completely use a GPU’s resources, the GPU cannot be efficiently shared between multiple applications, leading to GPU underutilization.

We present Salus to enable two GPU sharing primitives: fast job switching and memory sharing, to achieve fine-grained GPU sharing among multiple DL applications. Salus is an efficient, consolidated execution service that exposes the GPU to different DL applications, and it enforces fine-grained sharing by performing iteration scheduling and addressing associated memory management issues. We show that these primitives can then be used to implement flexible sharing policies. Our integration of Salus with TensorFlow and evaluation on popular DL jobs shows that Salus can improve the average completion time of DL training jobs by $3.19\times$, GPU utilization for hyper-parameter tuning by $2.38\times$, and GPU utilization of DL inference applications by $42\times$ over not sharing the GPU and $7\times$ over NVIDIA MPS with small overhead.

1 **Introduction**

Deep learning (DL) has received ubiquitous adoption in recent years across many data-driven application domains, ranging from machine translation and image captioning to chat bots and personal assistants (LeCun et al., 2015). Consequently, both industry and academia are building DL solutions – e.g., TensorFlow (Abadi et al., 2016), CNTK (Yu et al., 2014), and others (Dean et al., 2012; Chen et al., 2015; Paszke et al., 2019; Bergstra et al., 2011) – to enable both training DL models using large datasets as well as serving DL models for inference.

GPUs have emerged as a popular choice in this context because they excel at highly parallelizable matrix operations common in DL jobs (Jia et al., 2018; Zhu et al., 2016; Jouppi et al., 2017; Abadi et al., 2016). Unfortunately, the minimum granularity of GPU allocation today is often the entire GPU – an application can have multiple GPUs, but each GPU can only be allocated to exactly one application (Jeon et al., 2019). While such exclusiveness in accessing a GPU simplifies the hardware design and makes it efficient in the first place, it leads to two major inefficiencies.

First, the coarse-grained, one-at-a-time GPU allocation model$^1$ hinders the scheduling ability of GPU cluster managers (Gu et al., 2019; Xiao et al., 2018; Hindman et al., 2011; Bernstein, 2014; Vavilapalli et al., 2013; Dutta & Huang, 2019; NVIDIA, 2020b). For flexible scheduling, a cluster manager often has to suspend and resume jobs (i.e., preempt), or even migrate a job to a different host. However, a running DL job must fully be purged from the GPU before another one can start, incurring large performance overhead. As such, GPU clusters often employ non-preemptive scheduling, such as FIFO (Dutta & Huang, 2019; Jeon et al., 2019), which is susceptible to the head-of-line (HOL) blocking problem; or they suffer large overhead when using preemptive scheduling (Gu et al., 2019).

Second, not all DL jobs can fully utilize a GPU all the time ($\S$2). On the one hand, DL training jobs are usually considered resource-intensive. But for memory-intensive ones (e.g., with large batch sizes), our analysis shows that the average GPU memory utilization is often less than 50% ($\S$2.1) due to varied memory usage over time and between iterations. Similar patterns can also be observed in compute-intensive training jobs. DL model serving also calls for finer-grained GPU sharing and packing. Because the request rate varies temporally within the day as well as across models, the ability to hold many DL models on the same GPU when request rates are low can significantly cut the cost by decreasing the number of GPUs needed in serving clusters (Crankshaw et al., 2017; Migacz, 2017).

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Additionally, the increasingly popular trend of automatic hyper-parameter tuning of DL models (Bergstra et al., 2013; Li et al., 2016; Rasley et al., 2017) further emphasizes the need to improve GPU utilization. This can be viewed as “pre-training.” One exploration task usually generates hundreds of training jobs in parallel, many of which are killed as soon as they are deemed to be of poor quality. Improved GPU utilization by spatiotemporal packing of many of these jobs together results in shorter makespan, which is desirable because exploration jobs arrive in waves and the result is useful only after all jobs are finished.

We address these issues by presenting Salus, which enables fine-grained sharing of individual GPUs with flexible scheduling policies among co-existing, unmodified DL applications. While simply sharing a GPU may be achievable, doing so in an efficient manner is not trivial (§2.2). Salus achieves this by exposing two GPU sharing primitives: fast job switching and memory sharing (§3). The former ensures that we can quickly switch the current active DL job on a GPU, enabling efficient time sharing and preemption. The latter ensures high utilization by packing more small DL jobs on the same device. The unique memory usage pattern of DL applications is the key to why such primitives can be efficiently implemented in Salus: we identify three different memory usage patterns and apply different management policies when handling them (§3.2). Combining these two primitives, we implement a variety of GPU scheduling solutions (§4).

We have integrated Salus with TensorFlow and evaluated it on a collection of DL workloads consisting of popular DL models (§5). Our results show that Salus improves the average completion time of DL training jobs by 3.19× by efficiently implementing the shortest-remaining-time-first (SRTF) scheduling policy to avoid HOL blocking. In addition, Salus shows 2.38× improvement on GPU utilization for the hyper-parameter tuning workload, and 42× over not sharing the GPU and 7× over NVIDIA MPS for DL inference applications with small overhead.

2 BACKGROUND AND MOTIVATION

2.1 DL Workloads Characteristics

We analyzed a collection of 15 DL models (Table 2 in Appendix) to understand the resource usage patterns of DL jobs. This set of models are compiled from the official TensorFlow CNN benchmarks (TensorFlow, 2020) and other selected popular models in respective fields.

In order to cover a wider range of use cases, while keeping the native input characteristics, we varied the batch size to create 45 distinct workloads, as shown in Table 2. Note that the batch size specifies the number of samples (e.g., images for CNNs) trained in each iteration and affects the size of model parameters. Thus the larger the batch size, the longer it takes to compute an iteration. Throughout the paper, we uniquely identify a workload by the model name plus the input batch size. For example, alexnet_25 means a job training alexnet, with a batch size of 25.

In terms of GPU resource usage, one can consider two high-level resources: (i) GPU computation resources (primarily in terms of computation time, often referred to as GPU utilization in the literature) and (ii) GPU memory. We found that both are often correlated with the complexity of the DL model. However, GPU memory is especially important because the entire DL model and its associated data must reside in memory for the GPU to perform any computation; in contrast, computations can be staggered over time given sufficient GPU memory.

In the following, we highlight a few key GPU memory usage patterns in DL workloads that lead to memory underutilization issues and/or opportunities for improvements.

Heterogeneous Peak Memory Usage Across Jobs

DL workloads are known for heavy memory usage (Abadi et al., 2016; Li et al., 2014; Chilimbi et al., 2014). Figure 1 visualizes the average and peak memory usages of our workloads. As models become larger (with more and wider layers) and the batch size increases, memory requirements of DL jobs increase as well. For example, we observed peak memory usages as high as 13.8 GB for resnet152 and as low as less than 1 GB for vae. Such high variations suggest that even during peak allocation periods, it may be possible to run multiple models on the same GPU instead of FIFO.
Temporal Memory Usage Variations Within a Job

Within each job, however, each iteration of a DL training job is highly predictable with a well-defined peak memory usage and a trough in between iterations. Figure 2 shows an example. This is because DL jobs go through the same sequence of operations and memory allocations in each iteration. The presence of predictable peaks and troughs can help us identify scheduler invocation points.

Low Persistent Memory Usage

Another important characteristic of GPU memory usage of DL jobs is the use of persistent memory to hold parameters of a model – this corresponds to the consistent troughs across iterations. Even though the peak usage can be very high, most of it is temporary data created and destroyed within the same iteration. Fortunately, the size of persistent memory is often very low in comparison to the peak, ranging from 110.9 MB for googlenet.25 to 822.2 MB for resnet152.75. As long as the model parameter is already in GPU memory, we can quickly start an iteration of that model. This gives us an additional opportunity to improve sharing and utilization.

2.2 Existing Techniques for Sharing GPUs

Given that DL workloads leave ample room for GPU sharing, a straw man approach would be disabling the exclusive access mode and statically partitioning the GPU memory among DL jobs. This cannot completely address the under-utilization problem due to high peak-to-average memory usage of DL jobs.

NVIDIA’s Multi-Process Service (MPS) (NVIDIA, 2020a) can be used to speed up the static partitioning approach for GPU sharing by avoiding costly GPU context switches. Nonetheless, MPS has limited support for DL frameworks or companies’ in-house monitoring tool according to our experiments and various bug reports.

Static partitioning and MPS also fail to provide performance isolation. Co-located DL jobs can cause large and hard to predict interferences. A recent work, Gandiva (Xiao et al., 2018) approaches this by trial and error and fallback to non-sharing mode. Xu et al. (2019) propose to use machine learning model to predict and schedule GPU-using VMs in the cluster to minimize interferences.

NVIDIA’s TensorRT Inference server (Migacz, 2017) and the prior work by Samanta et al. (2019) achieve simultaneous DL inference in parallel on a single GPU. But they lack support for DL training.

Finally, earlier works on fine-grained GPU sharing fall into two categories. Some attempt to intercept GPU driver API calls and dynamically introduce concurrency by time-slicing kernel execution at runtime (Pai et al., 2013; Ravi et al., 2011; Park et al., 2015). Others call for new APIs for GPU programming (Suzuki et al., 2016; Yeh et al., 2017; Zhang et al., 2018). These solutions are designed for jobs with a few GPU kernels; as such, they are not scalable to DL applications, where the number of unique kernels can easily go up to several hundreds.

3 Salus

Salus is our attempt to build an ideal solution to GPU sharing. It is designed to enable efficient, fine-grained sharing while maintaining compatibility with existing frameworks (§3.1). Its overall design is guided by the unique memory usage characteristics of DL jobs. Packing multiple jobs onto one GPU changes the combined memory allocation patterns and special care must be taken to mitigate increased fragmentation, because existing DL frameworks are designed for the job-exclusive GPU usage scenario. Salus addresses both temporal and spatial aspects of the memory management problem by enabling two GPU sharing primitives:

1. Fine-grained time sharing via efficient job switching among ongoing DL jobs (§3.2);
2. Dynamic memory sharing via the GPU lane (§3.3).

Together, these primitives open up new scheduling and resource sharing opportunities. Instead of submitting one job at a time, which can easily lead to HOL blocking, one can perform preemption or run multiple DL jobs in a time- or space-shared manner – all of which can be utilized by a GPU cluster scheduler (Xiao et al., 2018; Gu et al., 2019).

Salus is available as an open-source software at https://github.com/SymbioticLab/Salus.
We demonstrate the possibilities by implementing common scheduling policies such as preempting jobs for shortest-
remaining-time-first (SRTF) or fair sharing, and packing many jobs in a single GPU to increase its utilization (§4).

3.1 Architectural Overview

At the highest level, Salus is implemented as a singleton execution service, which consolidates all GPU accesses, thus enabling sharing while avoiding costly context switch among processes on the GPU. As a result, any unmodified DL job can leverage Salus using a DL framework-specific adaptor (Figure 3).

From a framework’s point of view, the adaptor abstracts away low level details, and Salus can be viewed as another (virtual) computation device; From a user’s perspective, the API of the framework does not change at all. All scripts will work the same as before.

It is perhaps better to explain the architecture via an example of the life cycle of a DL job. When a job is created in an user script, Salus adaptor in the DL framework creates a corresponding session in Salus (1a). The computation graph of the DL job is also sent to Salus during the creation.

The session then proceeds to request a lane from the memory manager (1b). Depending on current jobs in the system, this process can block and the session will be queued (§3.3).

During the job’s runtime, either training or inferencing, iterations are generated by the user script and forwarded to the corresponding session in Salus (2a). They are then scheduled according to their associated GPU lanes by the iteration scheduler (2b), and send to GPU for execution.

The Salus execution service thus achieves GPU sharing via iteration-granularity scheduling of DL jobs. We elaborate on a performance-efficiency tradeoff in choosing this granularity (§3.2.2).

3.2 Efficient Job Switching

The ability to switch between jobs is paramount to implement time sharing and preemption – two techniques extensively used by modern schedulers in many contexts. Suspending a running job and resuming the same or another one have always been possible on GPU as well. Modern DL frameworks extensively use checkpointing to mitigate data and computation loss due to the long running nature of DL training jobs. The same technique is applied by Gandiva (Xiao et al., 2018) to achieve second-scale suspend/resume. Nevertheless, checkpointing can result in large data transfers from and to the GPU memory, even in the best case when only model parameters are transferred, the communication time is still non-negligible. It even becomes unacceptable if the system ever wants to support inference workloads: the theoretical minimal transfer time can be even several times longer than the inference latency itself, according to the measurement on our collection of workloads (Figure 4).

Observation 1 Transferring GPU memory back and forth is not practical to achieve low latency given current GPU communication bandwidth.

3.2.1 Characterizing DL Memory Allocations

We observe that one can push things further by taking a close look at different types of memory allocations in a DL job. Specifically, we define three types of memory allocations with unique characteristics.

1. Model: These mostly hold model parameters and typically consist of a few large chunks of memory. They are persistent because they have to be available throughout the whole job’s lifetime. Because the model size is typically fixed during the entire training process, model data has little or no temporal variations and is predictable.

2. Ephemeral: These are the scratch memory needed during each iteration. These memory usually hold intermediate layers’ outputs as well as temporary data generated by the algorithm itself. They are only needed during computations and are released between iterations, giving rise to the temporal memory usage patterns of DL
jobs. They are often large memory allocations as well.

3. Framework-internal: These are usually used by the DL framework for book-keeping or for data preparation pipeline. They often persist across iterations.

Collectively, model and framework-internal memory are persistent across iterations. As an example, Figure 5 gives the memory allocation size distribution for a popular CNN workload: inception3.

**Observation 2** There is significantly less persistent memory than ephemeral ones in a DL job. It is possible to keep more than one job’s persistent memory in GPU while still having enough space for either one’s ephemeral memory.

The above two observations naturally lead to the conclusion that fast job switching can be enabled by not removing persistent memory from GPU at all. Thus unlike existing works (Xiao et al., 2018), Salus is designed to enable significantly faster suspend/resume operations by keeping persistent memory around, and then an iteration-granularity job scheduler (e.g., time sharing or preemption-based) decides which job’s iteration should be run next.

### 3.2.2 Scheduling Granularity

Given that iterations are typically short in DL jobs (ranging from tens of milliseconds to a few seconds), with an even finer granularity, e.g., at the GPU kernel level, it may be possible to further utilize GPU resources. However, finer-grained scheduling also adds more overhead to the execution service. Indeed, there is a tradeoff between maximum utilization and efficiency for a given scheduling granularity.

To understand this tradeoff, we prototyped a GPU kernel-level switching mechanism as well only to find that scheduling at that level incurs too much overhead for little gain. It requires all GPU kernels to go through a central scheduler, which, in addition to becoming a single bottleneck, breaks common efficiency optimizations in DL frameworks such as kernel batching and pipelining.

![Figure 5](image)

**Figure 5.** Memory allocation distribution for ephemeral, model and framework-internal memory, measured using *inception3*.

3.3 Spatial Sharing via GPU Lane

Although DL jobs’ memory usages have spatiotemporal variations, many cannot reach the total capacity of a GPU’s memory. Naturally, we must consider ways to better utilize the unused memory.

Built on top of the efficient job switching, we design a special memory layout scheme, the *GPU Lane*, that achieves memory sharing and improves memory utilization.

First of all, learning from classic memory management techniques of stack and heap to separate dynamic allocations from static ones, we divide GPU memory space into *ephemeral* (Eph.) and *persistent* (Pst.) regions, growing from both end of the memory space (Figure 6a). A DL job’s ephemeral memory goes into the ephemeral region, while other types of memory is allocated in the persistent region.

The ephemeral region is further divided into *lanes*, which are continuous memory spaces that can contain ephemeral memory allocation for iterations. Lanes are not only about memory, though. Iteration execution is serialized within a lane and parallelism is achieved across lanes, which is implemented using GPU streams. Each lane can be assigned to multiple DL jobs, which are time-shared within the lane.

The lane’s restriction on execution is necessary because different from the other two types of memory, ephemeral allocations happens in small chunks and cannot be predicted ahead. As a result, simply putting two iterations together may cause deadlock because there is no swapping for the oversubscribed memory.

Even if enough memory is ensured for both peak memory usage for two iterations, memory fragmentation can still cause superfluous out-of-memory errors if not handled correctly. More specifically, while the framework-internal memory allocations are small in size, they can have a large impact on the overall memory layout and may create more memory fragments when multiple iterations are allocating simultaneously. While there are works implementing a memory planner before actually starting the iteration (Chen et al.,

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3The existing memory overcommit technique Unified Memory Access is too slow to use. See §5.4.
Algorithm 1 Find GPU Lane for Job

1: **Input:** $P$: the job’s persistent memory requirement  
   $E$: the job’s ephemeral memory requirement  
   $C$: total memory capacity of the GPU  
   $P_i$: persistent memory usage of existing job $i$  
   $L_j$: lane size of existing lane $j$  
   $\mathbb{L}$: set of existing lanes  
2: if $\sum_i P_i + P + \sum_j L_j + E \leq C$ then  
3:    lane $\leftarrow$ new GPU lane with capacity $E$  
4:    **return** lane  
5:    **end if**  
6:    for all $j \in \mathbb{L}$ do  
7:        if $L_j \geq E$ and is the best match then  
8:            **return** $j$  
9:        **end if**  
10:   **end for**  
11:   for $r \in \mathbb{L}$ in $L_r$ ascending order do  
12:      if $\sum_i P_i + P + \sum_j L_j - L_r + E \leq C$ then  
13:          $L_r \leftarrow E$  
14:      **return** $r$  
15:   **end if**  
16: **end for**  
17: **return** not found

Throughout the process, the following “safety” condition is always kept to make sure the persistent region and ephemeral region do not collide into each other:

$$\sum_{job \ i} P_i + \sum_{job \ j \ in \ l} \max (E_j) \leq C$$

where $P$ and $E$ are respectively the persistent (model and framework-internal) and ephemeral memory usage of a job. $C$ is the capacity of the GPU. The second term is the sum of all lanes’ size, which is defined as the maximum ephemeral memory usage of all jobs in the lane.

By ensuring enough capacity for persistent memory of all the admitted jobs and enough remaining for the iteration with the largest temporary memory requirement, Salus increases the utilization while making sure that at least one job in the lane can proceed.

Implementation-wise, the system is event-driven, and reacts when there are jobs arriving or finishing, or at iteration boundaries when auto defragmentation happens. The lane finding logic is shown in Algorithm 1, which outputs a suitable lane given a job’s memory requirement.

How to reorganize lane assignments is an open question. We find the one implemented in our algorithm works fairly well in practice, but there are more possibilities about finding the optimal number of lanes given a set of jobs.

4 Scheduling Policies in Salus

The state-of-the-art for running multiple DL jobs on a single GPU is simply FIFO, which can lead to HOL blocking. Although recent works (Xiao et al., 2018; Gu et al., 2019) have proposed time sharing, they enforce sharing over many minutes due to high switching overhead.

Thanks to its fine-grained GPU sharing primitives, Salus makes it possible to pack jobs together to increase efficiency, or to enforce any priority criteria with preemption. It opens up a huge design space to be explored in future works.

To demonstrate the possibilities, in our current work, we have implemented some simple scheduling policies, with Salus specific constrains (i.e., safety condition). The PACK policy aims to improve resource utilization and thus makespan, the SRTF policy is an implementation of shortest-remaining-time-first (SRTF), and the FAIR policy tries to equalize resource shares of concurrent jobs.

4.1 PACK to Maximize Efficiency

To achieve higher utilization of GPU resources, many jobs with different GPU memory requirements can be packed together in separate GPU lanes based on their memory usages. However, packing too many lanes exceeding the GPU memory capacity will either crash the jobs or incur costly
We have integrated Salus with TensorFlow and evaluated it using a collection of training, hyper-parameter tuning, and inference workloads (TensorFlow, 2020; Sutskever et al., 2014; Kingma & Welling, 2013; Shi et al., 2016; Hannun et al., 2014) to understand its effectiveness and overhead. The highlights of our evaluation are as follows:

Table 1. Makespan and aggregate statistics for different schedulers.

<table>
<thead>
<tr>
<th>Sched.</th>
<th>Makespan</th>
<th>Avg. Queuing</th>
<th>Avg. JCT</th>
<th>95% JCT</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIFO</td>
<td>303.4 min</td>
<td>167.6 min</td>
<td>170.6 min</td>
<td>251.1 min</td>
</tr>
<tr>
<td>SRTF</td>
<td>306.0 min</td>
<td>28.6 min</td>
<td>53.4 min</td>
<td>217.0 min</td>
</tr>
<tr>
<td>PACK</td>
<td>287.4 min</td>
<td>129.9 min</td>
<td>145.5 min</td>
<td>266.1 min</td>
</tr>
<tr>
<td>FAIR</td>
<td>301.6 min</td>
<td>58.5 min</td>
<td>96.6 min</td>
<td>281.2 min</td>
</tr>
</tbody>
</table>

Figure 7. CDFs of JCTs for all four scheduling policies.

5.1 Long-Running Training
We start by focusing on Salus’s impact on training. To this end, we evaluate Salus using a job trace of 100 workloads, generated using the jobs described in Table 2. We considered multiple batch sizes and durations of each training job in the mix. The overall distribution followed one found in a production cluster (Gu et al., 2019).

We compare four different schedulers:
1. FIFO refers to processing jobs in order of their arrival.
Salus: Fine-Grained GPU Sharing Primitives for Deep Learning Applications

This is the de facto mechanism in use today.

2. **SRTF** is a preemptive shortest-remaining-time-first scheduler. We assume that the duration is known or can be estimated (Peng et al., 2018).

3. **PACK** attempts to pack as many jobs as possible into the GPU. The goal is to minimize the makespan.

4. **FAIR** uses time sharing to equally share the GPU time among many jobs.

### 5.1.1 Overall Comparison

Figure 7 presents the distributions of JCTs for all four policies, while Table 1 presents makespan and aggregate statistics. Given the similarities of makespan values between FIFO, SRTF, and FAIR, we can conclude that Salus introduces little overhead. Furthermore, packing jobs can indeed improve makespan. Note that because of online job arrivals, we do not observe large improvement from PACK in this case. However, when many jobs arrive together, PACK can indeed have a larger impact (§5.2).

These experiments also reestablishes the fact that in the presence of known completion times, SRTF can indeed improve the average JCT – 3.19× w.r.t. FIFO in this case.

### 5.1.2 Impact of Fast Job Switching

We evaluate Salus’s ability to perform fast job switching in two contexts. First, we show that it allows cheap preemption implementation, which, in turn, makes possible the shortest-remaining-time-first (SRTF) scheduling policy. Second, we show fast job switching can achieve fair sharing among DL jobs in seconds-granularity – instead of minutes (Xiao et al., 2018). In both cases, we consider a single GPU lane.

**SRTF** Consider the following scenario: a large training job has been running for a while, then the user wants to quickly do some test runs for hyper-parameter tuning for smaller models. Without Salus, they would have to wait until the large job finishing – this is an instance of HOL blocking. Salus enables preemption via efficient switching to run short jobs and resumes the larger job later.

We pick a segment in the long job trace, containing exact the scenario, and record its detailed execution trace, showing in Figure 8a. When job #1 arrives, the background job #0 is immediately stopped and Salus switches to run the newly arrived shorter job. Job #2 comes early than job #3, but since #3 is shorter, it is scheduled first. And finally since job #5 is shorter, #4 is preempted and let #5 run to completion. During the process, the background job #0 is only scheduled when there is no other shorter job existing.

Figure 8b is another example demonstrating Salus’s ability to fast switch. It visualizes memory allocations in the scale of seconds: at the moment of a job switching, the second job’s iteration starts immediately after the first job stops.

**Time Sharing/Fairness** To better illustrate the impact of fairness, we show another microbenchmark, demonstrating Salus’s ability to switch jobs efficiently using 3 training jobs and focusing on the fair sharing of GPU throughput in Figure 9.

For ease of exposition, we picked three jobs of the same DL model, `inception3_50` – this allows us to compare and aggregate training throughput of the three models in terms of images processed per second. In this figure, in addition to the throughput of individual jobs, the black dashed line shows the aggregate throughput.

The training jobs start at time 0s, 15s and 30s. At 15s, when the second job starts, while the total throughput remains unchanged, each job’s share is halved. It further reduces
We evaluate two sets of hyper-parameter exploration jobs: resnet50 and superres, for image classification and resolution enhancement, respectively. Each set has 300 jobs, and each one completes after all 300 complete. A comparison of achieved makespan using FIFO (in TensorFlow) and Salus is shown in Figure 11. In the resnet50 case, there is 1.07× makespan improvement while it is 2.38× for superres.

Little improvement is seen for resnet50 because while the GPU has enough memory, computation becomes the bottleneck under such heavy sharing. Consequently, the makespan does not see much improvement.

5.3 Inference

So far we have only discussed DL training, but we note that serving a trained model, i.e., inference, can also be a good – if not better – candidate for GPU memory sharing. Rather than focusing on throughput when training, latency of individual inference request becomes a more important requirement when serving DL models (Crankshaw et al., 2017; Migacz, 2017).

In order to keep responsive to requests, DL models have to be online 24×7 hours. In the traditional setting, each model must reside on a dedicated GPU. However, the traffic of serving requests is not always constant throughout the day, and there are times when the request rate is significantly lower compared to peak. Consolidating DL models into fewer GPUs while remain responsive can save the maintains cost for service providers.

We demonstrate Salus’s ability to reduce the number of GPUs needed while maintaining reasonable response latency in Figure 10. 42 DL inference jobs are selected consisting of 14 different models, 3 instances for each model. Without MPS or Salus, 42 GPUs are needed to hold these DL models. In contrast, Salus needs only 1 GPU, achieving 42× improvement, while the average latency overhead is less than 5ms. For comparison, MPS needs 6 GPUs.

A future work is to detect current request rate for inference jobs and automatically scale up or down horizontally. Nevertheless, Salus provides the essential primitives that makes the implementation possible.

5.4 Overhead

Salus has to be efficient, otherwise the benefits gained from sharing can be easily offset by the overhead. Figure 12 shows per iteration training time in Salus, normalized by
We finally proceed to compare the performance to run (SP+MPS), and static partitioning with MPS and memory overcommit (SP+MPS+OC) solution has significantly bad performance that is beyond useful at the moment. Salus manages to achieve almost the same performance as MPS while providing much more flexibility in scheduling policy. As shown before, in lightly-loaded inference scenarios, it can significantly outperform MPS in terms of utilization.

The result confirms that MPS is indeed better than SP due to the avoidance of GPU context switching. Unfortunately, the SP+MPS+OC solution has significantly bad performance that is beyond useful at the moment. Salus manages to achieve almost the same performance as MPS while providing much more flexibility in scheduling policy. As shown before, in lightly-loaded inference scenarios, it can significantly outperform MPS in terms of utilization.

We finally proceed to compare the performance to run two jobs on a single GPU using existing solutions. Two alexnet 25 training jobs are started at the same time and each runs for a minute. The jobs share a single GPU using Salus, static partitioning (SP), static partitioning with MPS (SP+MPS), and static partitioning with MPS and memory overcommit (SP+MPS+OC). We collect and compare the average JCT and report the result in Figure 13.

The result confirms that MPS is indeed better than SP due to the avoidance of GPU context switching. Unfortunately, the SP+MPS+OC solution has significantly bad performance that is beyond useful at the moment. Salus manages to achieve almost the same performance as MPS while providing much more flexibility in scheduling policy. As shown before, in lightly-loaded inference scenarios, it can significantly outperform MPS in terms of utilization.

Figure 12. Per iteration time per workload in Salus, normalized by that of TensorFlow. Only the largest batch size for each model is reported, as other batch sizes have similar performance.

6 CONCLUDING REMARKS

GPUs have emerged as the primary computation devices for deep learning (DL) applications. However, modern GPUs and their runtimes do not allow efficient multiple coexisting processes in a GPU. As a result, unused memory of a DL job remains unaccessible to other jobs, leading to large efficiency, performance loss, and head-of-line (HOL) blocking.

Salus enables fine-grained GPU sharing among complex, unmodified DL jobs by exposing two important primitives: (1) fast job switching that can be used to implement time sharing and preemption; and (2) the GPU lane abstraction to enable dynamic memory partitioning, which can be used for packing multiple jobs on the same GPU. Together, they can be used to implement unforeseen new policies as well.

However, Salus is only a first attempt, and it opens many interesting research challenges. First, Salus provides a mechanism but the question of policy – what is the best scheduling algorithm for DL jobs running on a shared GPU? – remains open. Second, while not highlighted in the paper, Salus can be extended to multiple GPUs or even other accelerators on the same machine. Finally, we plan to extend it to GPUs across multiple machines leveraging RDMA.

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Salus: Fine-Grained GPU Sharing Primitives for Deep Learning Applications

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A WORKLOADS

Table 2 is the full list of workloads and their batch sizes we used in our evaluation.

Figure 14 is the same peak and average GPU memory usage measurement done in PyTorch, except overfeat, which we could not find a working implementation.

<table>
<thead>
<tr>
<th>Model</th>
<th>Type</th>
<th>Batch Sizes</th>
</tr>
</thead>
<tbody>
<tr>
<td>alexnet</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>googlenet</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>inception3</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>inception4</td>
<td>Classification</td>
<td>25, 50, 75</td>
</tr>
<tr>
<td>overfeat</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>resnet50</td>
<td>Classification</td>
<td>25, 50, 75</td>
</tr>
<tr>
<td>resnet101</td>
<td>Classification</td>
<td>25, 50, 75</td>
</tr>
<tr>
<td>resnet152</td>
<td>Classification</td>
<td>25, 50, 75</td>
</tr>
<tr>
<td>vgg11</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>vgg16</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>vgg19</td>
<td>Classification</td>
<td>25, 50, 100</td>
</tr>
<tr>
<td>vae</td>
<td>Auto Encoder</td>
<td>64, 128, 256</td>
</tr>
<tr>
<td>superres</td>
<td>Super Resolution</td>
<td>32, 64, 128</td>
</tr>
<tr>
<td>speech</td>
<td>NLP</td>
<td>25, 50, 75</td>
</tr>
<tr>
<td>seq2seq</td>
<td>NLP</td>
<td>Small, Medium, Large</td>
</tr>
</tbody>
</table>

Table 2. DL models, their types, and the batch sizes we used. Note that the entire model must reside in GPU memory when it is running. This restricts the maximum batch size we can use.

Figure 14. Average and peak GPU memory usage per workload, measured in PyTorch and running on NVIDIA P100 with 16 GB memory. The average and peak usage for vae is 156 MB, 185 MB, which are too small to show in the figure.

B ARTIFACT APPENDIX

B.1 Abstract

The artifact includes the server implementation of Salus, modified tensorflow, as well as modified tensorflow benchmarks used in the paper evaluation. This artifact requires NVIDIA GPU and CUDA.

B.2 Artifact check-list (meta-information)

- Algorithm: yes
- Compilation: G++7 with CMake
- Binary: Docker image available
- Run-time environment: Ubuntu 16.04 with CUDA 9.1 and CUDNN. Root access not required.
- Hardware: GPU with reasonable large memory
- Metrics: Job completion time
- Output: log files with provided parsing scripts
- How much disk space required (approximately)?: 100 GB
- How much time is needed to prepare workflow (approximately)?: 1 day
- How much time is needed to complete experiments (approximately)?: 1 week
- Publicly available?: yes
- Code licenses (if publicly available)?: Apache-2.0
- Workflow framework used?: none

B.3 Description

B.3.1 How to access

- Server implementation: https://github.com/SymbioticLab/Salus
- Tensorflow-salus: https://github.com/SymbioticLab/tensorflow-salus
- Benchmark: https://github.com/Aetf/tf_benchmarks

B.3.2 Hardware dependencies

The server code requires NVIDIA P100 GPUs.

B.3.3 Software dependencies

Ubuntu 16.04 OS with the following dependencies:

- g++@7
- cuda@9.1 with cudnn@7
- boost@1.66.0
- cppzmq@4.3.0
- zeromq@4.2.5
- nlohmann-json@3.1.2
- protobuf@3.4.1
- gperftools@0.7
- bazel@0.5.4
- Oracal JDK 8
To run inside docker, NVIDIA docker runtime is also needed: https://github.com/NVIDIA/nvidia-docker

B.3.4 Data sets
Benchmarking uses random generated dataset.

B.4 Installation
To simply run the server with prebuilt docker image:

docker run --rm -it registry.gitlab.com/salus/salus

B.4.1 Compilation
There are two separate parts that need to be built in order: tensorflow-salus and the salus server.

The easiest way is to follow the same instructions used to build Docker images. Starting from https://gitlab.com/Salus/builder, which is the base docker image for tensorflow-salus, one can follow the commands on a Ubuntu 16.04 system and have an environment similar to what is used in the container.

After creating the builder environment, build tensorflow-salus.

Bazel is needed for building tensorflow, so first install it from the Github release page: https://github.com/bazelbuild/bazel/releases/tag/0.5.4. We need version 0.5.4.

Our modified version of tensorflow uses a helper script to configure the build system. First run

    inv deps && inv init

to create the configuration file invoke.yml. Next, adjust the configuration file as needed. Most likely the GPU compute capabilities need to be changed. It is under the key TF_CUDA_COMPUTE_CAPABILITIES. Now the configuration can be used to update the build system and actually build the package:

    inv config
    inv build

After successfully building tensorflow, use the following command to install it into the current virtual environment

    inv install

Do not delete the source tree for tensorflow-salus, which is needed for building the Salus server. The detailed command can be found in the Dockerfile located at the root of the Salus repo.

B.5 Experiment workflow
Python scripts under the benchmarks folder can be used to drive experiments.

Some additional python packages are required, install them with pip install -r requirements.txt.

The driver can be invoked from the root folder in the Salus repo

    python -m benchmarks.driver expXXX

where expXXX the file expXXX.py under the directory benchmarks/exps/.

Use python -m benchmarks.driver --help to see all options. Most likely various paths need to be changed.

B.6 Evaluation and expected result
The figures included in the paper are generated using the following experiment scripts: card250, card260, card270, card271, card272, card274, card275, exp1, exp17, exp62.

After running the experiment, a folder named after the experiment will be created in the output log folder, containing txt log files that can be further parsed. A corresponding parse script located in scripts can then be used to parse the result.

B.7 Experiment customization
New experiment can be done by adding a new experiment script. Please refer to other scripts for the API.