HYDRA: A SYSTEM FOR LARGE MULTI-MODEL DEEP LEARNING

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ABSTRACT
Training deep learning (DL) models that do not fit into the memory of a single GPU is a vexed process, forcing users to procure multiple GPUs to adopt “model-parallel” execution. Unfortunately, sequential dependencies in neural architectures often block efficient multi-device training, leading to suboptimal performance. We present “model spilling”, a technique aimed at models such as Transformers and CNNs to move groups of layers, or shards, between DRAM and GPU memory, thus enabling arbitrarily large models to be trained even on just one GPU. We then present a set of novel techniques leveraging spilling to raise efficiency for multi-model training workloads such as model selection: a new hybrid of task- and model-parallelism, a new shard scheduling heuristic, and “double buffering” to hide latency. We prototype our ideas into a system we call HYDRA to support seamless single-model and multi-model training of large DL models. Experiments with real benchmark workloads show that HYDRA is over 7x faster than regular model parallelism and over 50% faster than state-of-the-art industrial tools for pipeline parallelism.

1 INTRODUCTION
Recent advances in deep learning (DL) architectures have improved accuracy in many domains, but they typically come at the cost of much higher model sizes. Natural language processing (NLP) is now awash with multi-billion parameter models such as BERT-Large (Devlin et al., 2018), GPT-3 (Brown et al., 2020), and Megatron-LM (Shoeybi et al., 2019). Interest in such large models is also growing in computer vision (e.g., (Dosovitskiy et al., 2020)) and for tasks bridging NLP and relational data (Yin et al., 2020). Unfortunately, GPU memory capacity growth has not kept pace, creating a new bottleneck in DL (Sohoni et al., 2019).

A common way of addressing this problem is “model parallelism” (Ben-Nun & Hoefler, 2018). Model-parallel execution first partitions the model into disjoint subsets known as “shards” and places them on multiple devices (GPUs), as Figure 1A illustrates. During execution, intermediates between model shards are exchanged between GPUs to emulate single-device training.

Unfortunately, the majority of DL models that necessitate model parallelism (e.g., Transformers) utilize a sequential architecture, that impedes parallel shard execution across forward and backward passes. This inter-shard ordering constraint enforces an execution order that results in massive GPU under-utilization and poor speedups. Besides, this approach also forces DL users to get multiple GPUs to even attempt using such models, raising costs.

Two recent works that improve upon regular model parallelism are FlexFlow (Jia et al., 2018), which hybridizes model and data parallelism, and “pipeline parallelism” such as in GPipe (Huang et al., 2018; Harlap et al., 2018; Narayanan et al., 2021). But FlexFlow was mainly designed to optimize parallelization strategies and reduce compute costs, not tackle memory limits. Model parallelism’s role in FlexFlow is primarily a dimension of an optimization space where execution speed is the ultimate goal. In this sense, FlexFlow’s goals are complementary to our focus of efficiently training larger-than-GPU-memory models.

Pipeline parallelism, on the other hand, was designed to achieve higher speedups on chain neural architectures, which does help in the large model setting. Pipelining exploits data access patterns in mini-batch stochastic gradient descent (SGD), staging out successive mini-batches across devices and overlapping compute on different shards so as to reduce idling. Unfortunately, this approach still suffers from idle periods, also called “bubbles”, due to shared dependencies between the backward and forward passes of different mini-batches. The issue is illustrated in Figure 1B.

In this paper, we present HYDRA, a new system for larger-than-memory DL model training that decouples scalability from parallelism to tackle both challenges from first principles. We identify analogies between challenges in larger-than-GPU-memory DL training and classic relational database management system (RDBMS) design. This al-
We formalize the scheduling problem of SHARP and propose a novel hybrid of task parallelism and model parallelism in this context we call “shard alternator task parallelism” (SHARP) to further optimize resource utilization. The deterministic nature of selection in Sharded-LRTF enables some precognition in scheduling, which naturally leads to our next optimization technique. A common trick in RDBMSs to hide data movement latency during spilling is “double buffering:” split DRAM into two buffers so that computation happens over one and future data is pre-loaded to the other. We bring this idea to DL systems by weaving it into Sharded-LRTF, allowing HYDRA to ‘double-buffer model shards on GPU memory and hide latency of model spilling.

Overall, HYDRA features a carefully thought out system design combining the right mix of both classical RDBMS-inspired techniques adapted to DL and novel techniques to solve our core problem. Our implementation on top of PyTorch also minimizes overheads across our layered optimization stack without needing to modify the internal code of PyTorch, helping ease practical adoption.

We evaluate HYDRA empirically on two standard large-model benchmark workloads and datasets: hyperparameter tuning for BERT-style models on the WikiText-2 dataset (Merity et al., 2016) and neural architecture evaluation for Vision Transformer (Dosovitskiy et al., 2020) on the CIFAR-10 dataset. HYDRA substantially outperforms prior art on an 8-GPU machine, e.g., 7.5x speedups over standard PyTorch model parallelism, 4x over both DeepSpeed and FlexFlow, and 50% faster than GPipe. HYDRA also reports the highest GPU utilization rates and offers near-linear speedups. It also scales well for various model sizes.

In summary, this paper makes the following contributions:

- To the best of our knowledge, this is the first paper to decouple scalability from parallelism for large-model DL training to study both from first principles.
- Inspired by RDBMSs, we present a suite of scaling and efficiency techniques rooted in automated model sharding and spilling.
- To optimize multi-model execution, we present a novel hybrid form of DL execution called SHARP that blends task parallelism and model parallelism, mitigating the key cons of both.
- We cast SHARP as a form of MQO and build a simple scheduler featuring an efficient greedy heuristic called Sharded-LRTF. We further hide shard movement latency with double buffering in Sharded-LRTF.
• We implement all of our ideas in a system we call HYDRA, on top of PyTorch without altering its internal code. A thorough empirical evaluation with real large-model workloads shows that HYDRA significantly outperforms prior industrial and open source tools.

2 RELATED WORK

Hybrid Parallelism and Pipeline Parallelism. Hybrid parallel approaches such as FlexFlow (Jia et al., 2018) exploit mixed model-data parallelism within a DL model. But they do not tackle our core issue of model scalability and they often force users to manually split models across devices. Some even call such a framework “memory oblivious” (Band, 2020). Our experiments show HYDRA is significantly faster than a careful manual model splitting in FlexFlow. Note that such manual splitting is not practical for most DL users; HYDRA automates that stage away. Pipeline parallelism (Huang et al., 2018; Harlap et al., 2018; Narayanan et al., 2021) reduces idle times by staging multiple mini-batch computations across devices. But it confutes parallelism with scalability, forcing users to get many GPUs. By decoupling scalability from parallelism, HYDRA can scale to large models with even just one GPU. Finally, none of the prior art exploit the higher degree of parallelism inherent in multi-model training such as model selection workloads. We devise new hybrid parallelism techniques from first principles for this setting. That said, our techniques are complementary to both FlexFlow and pipeline parallelism under certain conditions; we leave it to future work to unify them all.

Reducing model memory footprints has received much attention in DL systems (Chen et al., 2016; Gruslys et al., 2016; Kumar et al., 2019; Jain et al., 2019; Jia et al., 2019). That goal is orthogonal to ours. ZeRO and DeepSpeed (Rajbharti et al., 2020) propose a data parallelism ‘technique for reducing memory footprints by sharing model state across data-parallel instances — this does not, however, address our core challenge of scalability and multi-model training. Other work on machine teaching (Wang et al., 2021) and data distillation (Wang et al., 2018) aims to minimize the memory footprints of data, but these techniques address a different aspect of memory in DL systems. While all these memory-reduction techniques address an orthogonal challenge, they could eventually be infused into HYDRA in the future to reduce the number of shards created.

Multi-query optimizations for DL systems are techniques to optimize ML systems by exploiting multi-model execution, e.g., systems such Cerebro (Kumar et al., 2021), Model-Batch (Narayanan et al., 2018), and ASHA (Li et al., 2018). Cerebro proposes a hybrid parallelism scheme named MOP combining task parallelism and data parallelism, akin to (but different from) SHARP’s hybrid model-task parallelism. ModelBatch raises GPU utilization by altering the DL tool’s internal execution kernels. None of them tackle larger-than-GPU-memory models, which is our focus. Other examples of MQO for DL systems are Krypton (Nakandala et al., 2020) and HummingBird (Nakandala et al., 2020) but they focus on inference, not training.

We presented an early version of this work at a non-full length (2 page) venue (Nagrecha, 2021). In that article, we explained the basic ideas of model sharding and spilling, outlined how task parallelism can be exploited for multi-model training, and proposed a vision for our system. This paper realizes that vision to build HYDRA, fleshes out SHARP, dives deeper into our scheduling formulation, and proposes the Sharded-LRTF and double buffering optimizations. This paper also presents a thorough empirical evaluation on real DL workloads.

3 OVERVIEW OF HYDRA

HYDRA is designed to be a lightweight wrapper around the popular DL tool PyTorch.1 We do not need any internal code of the DL tool to be altered, which can help ease practical adoption. Figure 3 illustrates the overall architecture of HYDRA and how it handles DL models.

HYDRA takes PyTorch models and dataloaders as input. The standard PyTorch APIs can be used for model definitions — no special annotation effort is required. Neural architectures are then automatically inferred by HYDRA. HYDRA then proceeds to ascertain the memory capacity of available GPUs, then automatically partitions the model(s) given into a queue of shards, with each shard-task respecting memory constraints. Section 4.1 explains this sharding process in more detail.

Model shards are then placed onto DRAM. HYDRA then begins sharded execution, applying SHARP to simultaneously employ all GPUs by executing different shards of different models in parallel. The scheduling algorithm selects which model will be trained next, and the shard at the front of its queue is then promoted into a buffer space in GPU memory. As soon as the GPU is free, the shard then begins training, already prepared and ready in memory. Upon completion, the shard is returned to DRAM and placed at the back of the model’s queue. Intermediate outputs are either held in memory or returned to DRAM depending on whether the next buffered shard can use them or not. As the queue loops, it is refreshed with new mini-batches from the dataloader so as to complete epochs.

The entire process relies on the memory-independence be-

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1It is straightforward engineering effort to add support for TensorFlow too but we skip it in our current version for tractability.
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Figure 3. Overall system architecture of HYDRA. It takes as input a user-specified set of models. It partitions the models automatically and assigns shards to GPUs according to its Scheduler. DRAM is used to temporarily store inactive model shards and inter-shard outputs.

4 MODEL SPILLING

We observe that it is an overkill to maintain all model shards across multiple GPUs at all times, as is done in regular model parallelism or pipeline parallelism. This is because sequential dependencies across layers in a neural architecture mean only one device (or a few) are really fully “active” with heavy computations at any point in time. Other devices act as mere repositories for “inactive” model shards.

Exploiting the above observation, we propose the following for inactive shards in HYDRA: spill them to DRAM. Only active shards are promoted to a GPU’s memory; the rest “wait” in DRAM. This is akin to sharding a table to stage reads between disk and DRAM in RDBMSs, except we are at a level higher in the memory hierarchy and focus on DL models instead. All this means HYDRA can scale to virtually arbitrarily large DL models on a single device, e.g., even a trillion-parameter model can be trained with just one GPU out of the box. This can already make a big difference for DL users with limited resources, e.g., for academic DL researchers or NLP applications in small enterprises.

4.1 Automated Model Partitioning

Both traditional model parallelism and our model spilling depend on some sort of “cut point” to split the neural computational graph because shards must consist of disjoint subsets of layer groups. Prior art (Narayanan et al., 2021) use some basic heuristics, albeit restricted to a specific class of models. Unfortunately, their approach is not general enough for our purpose. While one could use sophisticated graph partitioning algorithms for “optimal” partitioning, we find that is not worthwhile for two reasons. First, this stage is anyway only a tiny part of the overall runtime, which is dominated by the actual training runs. Second, due to the marginal utility of over-optimizing here, it will just make system engineering needlessly complex.

We prefer simplicity that still offers generality and good efficiency. Thus, we use a dynamic greedy approach based on toy “pilot runs.” Algorithm 1 presents it succinctly. The basic idea is to pack as much of a model as possible on to a GPU. If the set of GPUs is heterogeneous, we use the smallest-memory GPU to ensure cross-device compatibility of shards. We treat a DL model as an ordered list of layer indices, with the layers being “cut-points” in the graph to enable smooth partitioning. HYDRA then iterates through these indices to run “toy” passes with a single mini-batch once. If the run is successful, the Partitioner raises the

Algorithm 1 Dynamic model partitioning algorithm.

| Input: | Model as a sequence of layers $L$ with size $m$; data mini-batch $B$; GPU $G$ |
| Output: | Array of partition indices $A$ |
| Append 0 to $S$ |
| for $i = 0$ to $m - 1$ do |
| Place $L[i]$ and $B$ on $G$ |
| $B' \leftarrow$ Forward pass through $L[i]$ with $B$ |
| $T \leftarrow$ New tensor with same shape as $B'$ |
| Backpropagate $T$ through $L[i]$ without freeing its memory |
| if $G$ out of memory then |
| Append $i$ to $S$ |
| for $j = 0$ to $i - 1$ do |
| Release all memory consumed by $L[j]$ |
| Append $i$ to $A$ |
| end for |
| end if |
| end for |

2One can also easily spill further to disk if really needed.
We now present one of our key novel techniques: Shard Alternator Parallelism (SHARP), a hybrid of classical model parallelism and task parallelism to improve resource efficiency. We define our basic unit of computation, shard unit, as follows: the subset of computations of a forward or backward pass on a model’s shard. Thus, a full forward or backward pass of a model is a sequence of shard units. Overall, the scheduling goal is to execute all shard units of all models given by the user for all epochs.

Figure 5 illustrates the basic idea of SHARP contrasted with both task- and model parallelism. After a model’s shards are created (Section 4.1), shard units are naturally set. The key difference in SHARP is that a given model’s shard units do not necessarily run immediately after one another, i.e., they may be staggered over time. This is the key reason for SHARP’s higher efficiency—it breaks tasks down andreassembles them in a “better” way.

While the basic idea of SHARP is simple (but novel), realizing it in a working system poses two technical challenges: (1) the sheer number of shard units, and (2) the latency of swapping shards between device memory and DRAM. First, note that the number of shard units to be handled is multiplicative in 4 quantities: number of models given by the user, number of shards per model, number of mini-batches per epoch, and number of epochs per model training run. In realistic DL scenarios, one can easily hit tens of millions of shard units!

5.1 Automated Shard Orchestration

To realize SHARP in an system, we must handle 3 kinds of “data” before, during, and after a shard unit: (1) training data mini-batch, (2) model parameters, and (3) intermediate data/outputs of a shard unit. Thankfully, DL tools like PyTorch offer APIs that enable Data to be transferred from GPU memory to DRAM and vice versa. We use those APIs...
in HYDRA under the hood to automate shard orchestration. Each model is defined as a “queue” of shards in DRAM, ordered according to the neural computational graph. Each shard maintains the prepared data that will need to be used with the “next” shard. This data could include the training data mini-batch, intermediate data exchanged between shards, and/or gradients sent backward. The shard at the front of the queue is transferred to GPU memory along with its associated data to begin running that shard unit.

After shard unit execution completes, the inputs it used are discarded. The shard parameters (possibly updated) are returned to DRAM. In addition, the shard’s intermediate outputs, say, a gradient vector or a loss value, are also written to DRAM and attached to the model. They will be used as inputs for the model’s next shard. The last shard of a model concludes a full mini-batch training pass; after that, the old mini-batch is discarded and the next mini-batch of the prepared data will be used.

5.2 Double Buffering

A common trick used in RDBMSs, e.g., for external merge sort, is double buffering (Ramakrishnan & Gehrke, 1996). The basic idea is this: the processor’s memory (higher in the memory hierarchy) is split into two regions: one for active processing and the other as a “loading zone” for the next task. We bring this trick to the DL systems world for the first time. HYDRA uses it to mask shard loading latencies. We protect a “buffer space” in GPU memory during model partitioning (Section 4.1) to guarantee that so much buffer memory will be available during training. The buffer size is 15% by default, but users can adjust it if they like.

When our Scheduler picks the next shard to be run, we transfer it to that GPU’s buffer space even as the previous shard unit is running there. We load only what will fit into the buffer space. Usually, this is feasible because a model shard alone is often not that big—it is the combination with training data and massive intermediate outputs that causes memory pressure in large-model DL.

Interestingly, our double-buffered DL training in HYDRA also offers a serendipitous new bonus: we can avoid spilling (to DRAM) altogether in some cases. When a model’s shard unit it active, if its next shard is double-buffered on another GPU, we send intermediates with a fast GPU-to-GPU transfer instead of a slower GPU-to-DRAM-to-GPU route. Going further, if the next shard is double-buffered on the same GPU, intermediates need not move out of the GPU at all, substantially reducing latency.

Overall, while we focus on the GPU memory-DRAM dichotomy, our above techniques are general enough to be applicable across the entire memory hierarchy: between DRAM and local disk, local and remote disk, etc.

### Table 1. Notation for our scheduling formalization.

| Symbol | Description |
|--------|-------------|
| $T$    | List of models to be trained. |
| $P$    | List of devices (GPUs) available for training. |
| $M_i \in \mathbb{Z}^+$ | $M_i$ is the total shard unit count for model $T_i \in T$. Note that this covers all mini-batches (and potentially epochs). |
| $S_i \in \mathbb{R}^{M_i}$ | $S_i$ is a variable-length list of shard unit runtimes for model $T_i$. The runtime of shard unit $j$ is denoted as $S_{i,j}$. |
| $X_i \in \mathbb{R}^{|P| \times |M_i|}$ | $X_i$ is a variable-shape matrix of start times of shard units of model $T_i$ across workers. The start time of shard unit $j$ on worker $p$ is denoted as $X_{i,p,j}$. |
| $Y_i \in \{0, 1\}^{|P| \times L \times L}$ | $L$ is the total number of shard units across all models, i.e., $L = \sum_i M_i$, indexed cumulatively by the index of model $i$ and its shard unit $j$ (denoted $i,j$). $Y_{p,i,j',j''} = 1$ $\iff$ $X_{i,p,j} < X_{i',p,j''}$. |
| $U$    | An extremely large value used to enforce boolean logic. |

5.3 Scheduling Formalization of SHARP

The sheer number and variable runtimes of shard units across models necessitates a rigorous automated Scheduler. We immediately face three technical challenges. First, different models may train for different numbers of epochs, say, due to convergence-based SGD stopping criteria or early stopping in AutoML heuristics. Second, it is possible different devices have different compute capacities. Third, devices may disappear over time, say, due to faults, or get added, say, due to elasticity. Due to all these reasons, we choose a dynamic scheduling approach to place shard units on devices as and when a device becomes available over time. This design decision tackles all three challenges above in a unified way and also simplifies system implementation.

Specifically, we formalize our problem for a given set of epochs per model at a time. This may mean one epoch at a time or a pre-fixed number of epochs the user gives per model. Regardless, we treat each model to be trained as a queue of shard units unifying reasoning of division within a mini-batch, across mini-batches within an epoch, and across epochs.
5.3.1 Formal Problem Statement as MILP

The scheduling problem is as follows. At a given point in time, when a device (GPU) becomes available, a shard unit must be selected from one of the model’s queues to be placed upon that device. Shard units become eligible for scheduling if they have no pending dependencies, i.e., they are at the front of their queue and no other shard unit of that same model is still running on another device. The Scheduler’s job then is to pick a shard unit from the set of eligible shard units. Double-buffered training is already factored into this formulation: the Scheduler is actually picking shard units for double-buffering, and they get promoted from the buffer to compute.

All shard unit runtimes are given as input. Recall from Section 4.1 that the partitioner records this data during its pilot run. These runtimes may not be fully accurate due to variable system factors during execution, but are sufficient for effective scheduling. We now present the formal scheduling problem as an MILP. Table 1 explains our notation.

Objective: \( \min_{X,Y} C \) \hspace{1cm} (1)

Constraints:

\[
\forall t, t' \in [1, \ldots, |T|] \quad \forall p, p' \in P
\]

(a) \( \forall j \in [2, \ldots, M_t] \quad X_{t,p,j} \geq X_{t,p',j-1} + S_{t,j-1} \)

(b) \( \forall j \in [1, \ldots, M_t] \quad \forall j' \in [1, \ldots, M_{t'}] \quad X_{t,p,j} \geq X_{t',p,j'} + S_{t,j'} - (U \times Y_{p,t,j,t',j'}) \)

(c) \( \forall j \in [1, \ldots, M_t] \quad \forall j' \in [1, \ldots, M_{t'}] \quad X_{t,p,j} \leq X_{t',p,j'} - S_{t,j} + (U \times (1 - Y_{p,t,j',t',j'})) \)

(d) \( \forall j \in [1, \ldots, M_t] \quad X_{t,p,j} \geq 0 \)

(e) \( \forall j \in [1, \ldots, M_t] \)

(f) \( C \geq X_{t,p,j} + S_{t,j} \)

The objective is to pick a shard unit that can minimize makespan (completion time of the whole workload at this granularity). Constraints (a) simply enforce the sequential ordering of shard units within a model. Note that this set per model here is unified within a mini-batch, across mini-batches within an epoch, and potentially across epochs too—they are all sequentially dependent. Constraints (b) and (c) enforce model training isolation, i.e., only one shard unit can run on a device at a time. Constraints (d) is just non-negativity of start times, while Constraints (e) define the makespan.

Using a MILP solver such as Gurobi (Gurobi Optimization, 2021) enables us to produce an “optimal” schedule in this context. But the above task is a variant of a general job-shop scheduling problem described in (Ullman, 1975), and it is known to be NP-complete. Given that the number of shard units can span thousands to tens of millions, solving it optimally will likely be impractically slow. Thus, we look for fast and easy-to-implement scheduling algorithms that can still offer near-optimal makespans.

5.3.2 Intuitions on Scheduling Effectiveness

We observe that there are 2 primary cases encountered by a scheduler in our setting:

1. The number of models is equal to or greater than the number of available devices.
2. The number of models is less than the number of available devices.

In case (1), there will always be at least one eligible shard unit for each device at every scheduling decision. Any shard-parallel scheduling algorithm that accounts for all devices can easily keep all devices busy most of the time, i.e., busy waiting is unlikely. In case (2), all models can be trained simultaneously. Since each model’s shard unit uses at most one device in SHARP, and since there are more devices than models, there is no contention for resources here. In this case, regular task parallelism-style scheduling suffices and the makespan will just be the runtime of the longest “task.”

In both the cases above, even basic randomized scheduling might yield reasonable makespans. However, what it will not take into account is that case (1) is not static. Over time, as models finish their training, our setting may “degrade” from case (1) to case (2). Thus, two different schedulers that operate on a workload in case (1) may differ in their effectiveness based on how gracefully they degrade to case (2). As noted before, the makespan in case (2) scenario is determined solely by the longest-running remaining model. This gives us an intuition for a simple scheduler that can often do better than randomized: minimize the maximum remaining time among the remaining models.

In most realistic DL model selection workloads, overall completion time will be dominated by case (1). Thus, the marginal utility of pursuing an overly optimized Scheduler is low given the likely higher implementation complexity. However, if degradation to case (2) occurs earlier on, and if there is a substantial differences in task runtimes post-degradation, the overall completion times can differ more significantly based on the scheduling. Such degradation can arise in model selection workloads that use early stopping for underperforming models, e.g., Hyperband (Li et al., 2016), or by manual user intervention. Thus, we aim for a scheduling algorithm that can address such cases too in a unified way.

We propose a simple and practical greedy heuristic we call Sharded Longest Remaining Time First (LRTF) based on
Table 2. Details of end-to-end workloads. *Architectures similar to BERT-Large and ViT, scaled up for demonstration.

| Dataset   | Model Architectures | Model Sizes          | Batch Size | Learning Rate       | Epochs |
|-----------|---------------------|----------------------|------------|---------------------|--------|
| WikiText2 | BERT-Large*         | 1B                   | 8, 16, 32  | $10^{-3}, 10^{-4}$, $10^{-5}, 10^{-6}$ | 4      |
| CIFAR-10  | ViT*                | 300M, 600M, 800M, 1B, 1.5B, 2B | 64, 128    | $10^{-3}$           | 5      |

Algorithm 2 The Sharded-LRTF scheduling algorithm.

Struct

- Remaining epochs \( e \)
- Minibatches per epoch \( b \)
- Remaining minibatches in current epoch \( ce \)
- Minibatch training time \( t \)
- Remaining train time in current minibatch \( cm \)

Input: Idle Models \([M]\)
Output: Model \( MaxModel \)
\( MaxTrainTime = 0 \)

for Index \( i \), Model \( m \) in \([M]\) do

- \( ModelTrainTime = (m_e - 1) \times m_b + m_ce - 1 \) \times \( m_t + m_cm \)
- if \( ModelTrainTime > MaxTrainTime \) then
  - \( MaxTrainTime = ModelTrainTime \)
  - \( MaxModel = m \)
- end if
end for

5.3.3 Our Scheduling Algorithm: Sharded-LRTF

To quantitatively understand the effectiveness of Sharded-LRTF, we compare it using simulations against a basic randomized schedule and a Gurobi-output “optimal” schedule. For tractability, we set a timeout of 100s for Gurobi. We who both a homogeneous setting (all neural architecture are identical) and a heterogeneous setting, wherein they differ significantly. We assume all GPU devices are identical for simplicity, but that is also common in practice. Per-epoch runtimes of a model in the homogeneous setting are all fixed to 2 hours each, with 2000 shard units each. For the heterogeneous setting, per-epoch model runtimes are set between 30 minutes to 4 hours; number of shard units are

4In fact, an alternate data structure to record shard references can enable even constant-time selection.

set between 100 to 10,000. We randomly sample an initial set and report the average and standard deviations of 3 runs on the fixed set. Variance occurs due to non-deterministic scheduling behaviors from random selection and Gurobi timeout. Figure 6 shows the results.

MILP “optimal” has higher makespan in some cases because Gurobi did not converge to the global optimal in the given time budget. The randomized approach matches it or performs worse in many cases. But Sharded-LRTF matches or significantly outperforms the other approaches, especially in the heterogeneous setting. Also note that the runtime of Sharded-LRTF is in the order of tens of milliseconds, ensuring it is practical for us to use in HYDRA repeatedly for scheduling shard units on devices dynamically. Note that the actual mini-batch training computations on the device dominate overall runtimes.

6 Experiments

We now compare HYDRA against state-of-the-art open source and industrial tools for large-model DL training: PyTorch Distributed, Microsoft’s DeepSpeed, FlexFlow from Stanford/CMU, and Google’s GPipe idea. FlexFlow requires some manual guidance by editing the system-generated parallelism strategy file to ensure memory errors do not occur. We also show multiple variants with Deep-
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Speed, including superimposing a hybrid task parallelism (note that regular task parallelism is not applicable) and a hybrid data parallelism offered by DeepSpeed. We then dive into how HYDRA performs when various workload and system parameters are varied.

Workload Details. We use two popular DL model selection scenarios: hyperparameter evaluation and neural architecture evaluation. Table 2 lists details. For hyperparameter evaluation, we focus on masked-language modeling with the Transformer architecture BERT-Large (Devlin et al., 2018), trained on the benchmark WikiText-2 dataset. The neural architecture is fixed and we vary batch size and learning rate as key hyperparameters to create a total of 12 models to train, each with 1B parameters. For neural architecture evaluation, we focus on an emerging computer vision task with variants of the Vision Transformer (ViT) model (Dosovitskiy et al., 2020). We use the benchmark CIFAR-10 dataset. We create models with sizes between 600M parameters and 2B parameters. We also vary batch sizes, leading to a total of 12 models again.

Machine Setup. We focus on the single-node multi-GPU setting, anecdotally the most common among DL practitioners (although nothing in HYDRA prevents generalizing to multi-node clusters in the future). We use 8 GPUs, each being GTX 1080Ti’s with 11GB memory. The machine has 512 GB of DRAM and an Intel Xeon CPU with 10 2.20GHz cores, and it runs Ubuntu 18.04.

6.1 End-to-End Workloads

Figure 7 presents overall runtimes and GPU utilization results. We find that the baseline off-the-shelf PyTorch Distributed and DeepSpeed model parallelism report massive resource under-utilization. Thus, their runtimes are the highest. The basic hybrids with data- or task-parallelism do provide higher utilization and some modest speedups, but the fundamental limitations of model parallelism persist with such approaches, such that they still fall substantially short of ideal linear speedup (8x in this case). GPipe-style pipeline parallelism is much better, with about a 5x speedup against regular model parallelism. But HYDRA is the most efficient approach overall, reaching about 7.5x, close to the physical upper bound. The average GPU utilization of HYDRA is also the highest at over 80%.

6.2 Drill Down Analysis of HYDRA

We now dive into how HYDRA performs when varying key parameters from both ML and system standpoints. For reference sake, we also show standard model parallelism of PyTorch Distributed alongside.

6.2.1 Impact of Model Scale.

We vary the scale of the models to see the impact on relative performance of HYDRA. We fix the number of GPUs at 8 and the number of models to 12. Figure 8 shows the results. We see that HYDRA’s speedups over regular model parallelism is fairly consistent even as the model scale grows. This is because our partitioning approach (Section 4.1) and the dynamic Sharded-LRTF algorithm (Section 5.3) together ensure that shard unit times are similar even as model scale grows; basically, it just leads to more shard units to run. Our SHARP and double-buffering techniques further ensure that having more shard units do not cause relatively more resource idling on average.

Figure 8. Impact of model scale. Runtimes normalized to the first instance of regular model parallelism for clarity.

6.2.2 Impact of Number of GPUs.

We now study how varying the number of GPUs affects HYDRA’s speedup behavior. We fix the workload to 4 Transformer models, each with 250M parameters. We choose only 4 models to showcase both regimes: when the number of devices is less than models and vice versa. Figure 9
show the results. We see that HYDRA exhibits a roughly linear speedup when there are more models than devices. And when that flips, since HYDRA runs out of models to schedule, the speedup flattens as the degree of parallelism is limited. This flattening in the fewer-models regime is inherited from task parallelism by SHARP. We believe further hybridization of SHARP with data parallel training can help boost speedups and resource utilization in this regime; due to its complexity, we leave it to future work.

![Figure 9. Varying the number of GPUs. Speedups are normalized to standard model parallelism.](image)

### 6.2.3 Impact of Number of Models.

We now vary the number of models that are trained together. The number of GPUs is set to 8; all models have are uniformly large, at 250M parameters (same Transformer workload as before). Figure 10 shows the results. We see that HYDRA exhibits close to 8x speedups when the number of models is 8 or more but lower than that, the speedup is capped close to the actual number of models. As before, this too is due to SHARP inheriting the degree of parallelism from task parallelism. The GPU utilization numbers vary proportionally to the speedups seen.

![Figure 10. Varying the number of models trained together. Speedups are normalized to standard model parallelism.](image)

### 6.2.4 Ablation Tests.

In this experiment, we explore the effect of system components on framework performance. The number of devices is fixed to 8, with 16 Transformer models. All optimization levels include model spilling as a baseline, as this technique is critical to HYDRA’s basic operations. Table 3 demonstrates the results.

Pure model spilling dramatically slows down model training. This is only to be expected, given that it introduces a dependency on DRAM. SHARP’s throughput improvements dominate the slowdowns of model spilling, but it is important to note that SHARP’s speedups are workload-dependent. Double-buffering largely eliminates the cost of model spilling, enabling further speedups.

### 7 Limitations and Future Work

HYDRA currently has two key workload limitations, which we had assumed to ensure tractability. We aim to relax these in future work and generalize to more DL workloads.

#### Non-Sequential Architectures.

Just like pipeline-parallel systems, HYDRA focuses on models that are largely a sequence of layers (some branching is fine). Thankfully, the most critical GPU-memory-bottlenecked models in modern DL, viz., Transformers, satisfy this assumption. But note that HYDRA also supports large CNNs and MLPs out of the box today. Recurrent neural networks (RNNs) and graph neural networks (GNNs) have more complex dependencies across shard units, and we leave it to future work to study those model families in depth.

#### Data Parallelism.

When there are more models than devices, HYDRA already achieves near-optimal speedups. But if there are fewer models than devices, HYDRA may underutilize the devices due to a limitation inherited from task parallelism. Hybridizing data parallelism with SHARP can raise resource utilization in this regime. We leave such sophisticated hybrid-of-hybrids parallelization to future work.

### 8 Conclusion

Training larger-than-GPU-memory DL models is an increasingly critical need for DL users. Yet the existing landscape of “model parallelism” tools offers subpar scalability and parallelism, while often massively underutilizing GPUs. We present HYDRA, a new system for large-model DL training inspired by the design and implementation of RDBMSs. We identify a judicious mix of data systems techniques—some novel and some classical RDBMS ideas adapted to DL (such as sharding, spilling, and double buffering)—to enable large-model training even on a single GPU. By further exploiting the high degree of parallelism in multi-model training, we devise a novel hybrid parallel execution technique inspired by multi-query optimization. Our work offers practical benefits to DL practitioners, opens new lines of investigation in model parallelism research, and shows that the DL systems world can benefit from learning from the RDBMS world on data systems techniques to enable more seamless scalability and parallelism for DL workloads.
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