Cerebro: A Data System for Optimized Deep Learning Model Selection

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ABSTRACT

Deep neural networks (deep nets) are revolutionizing many machine learning (ML) applications. But there is a major bottleneck to wider adoption: the pain and resource intensiveness of *model selection*. This empirical process involves exploring deep net architectures and hyper-parameters, often requiring hundreds of trials. Alas, most ML systems focus on training one model at a time, reducing throughput and raising overall resource costs; some also sacrifice reproducibility. We present CEREBRO, a new information system architecture to raise deep net model selection throughput at scale without raising resource costs and without sacrificing reproducibility or accuracy. CEREBRO uses a new parallel SGD execution strategy we call *model hopper parallelism* that hybridizes task- and data-parallelism to mitigate the cons of these prior paradigms and offer the best of both worlds. Experiments on large ML benchmark datasets show CEREBRO offers 3x to 10x runtime savings relative to state-of-the-art data-parallel systems like Parameter Server and Horovod and up to 8x memory/storage savings relative to task-parallel systems. We also enable support for heterogeneous resources and fault tolerance in CEREBRO.

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1. INTRODUCTION

Deep learning is revolutionizing many ML applications. Their success at large Web companies has created excitement among practitioners in other settings, including domain sciences, enterprises, and small Web companies, to try deep nets for their applications. But training deep nets is a painful empirical process, since accuracy is tied to the neural architecture and hyper-parameter settings. A common practice to choose these settings is to *empirically compare as many training configurations as possible* for the user. This process is called *model selection*, and it is *unavoidable* because it is how one controls underfitting vs. overfitting [58]. Model selection is a major bottleneck for the adoption of deep learning among enterprises and domain scientists due to both the *time spent* and *resource costs*. Not all ML users can afford to throw hundreds of GPUs at their task and burn resources like the Googles and Facebooks of the world.

Case Study. We present a real-world model selection scenario. Our public health collaborators at UCSD want to develop deep learning-based models for identifying different human activities (e.g., sitting, standing, stepping, etc.) of subjects from body-worn accelerometer data. The data is collected from a cohort of 600 people and has a raw data size of 864 GB. During model selection, they want to try different deep net architectures such as convolution neural networks (CNNs), long short-term memory models (LSTMs), and composite models such as CNN-LSTMs, which have recently shown state-of-the-art results for multivariate time-series classification [33, 51]. They also want to explore different prediction window sizes (e.g., predictions generated at every 5 seconds vs. 15 seconds) and different data labeling schemes (e.g., sitting, standing, and stepping vs. sitting and not sitting). Furthermore, the deep learning training process also involves tuning various hyper-parameters such as learning rate and regularization coefficient.

In the above scenario it is clear that the model selection process generates dozens, if not hundreds, of different models that need to be evaluated in order to pick the best one for the prediction task. Due to the scale of the data and the complexity of the task, it is too tedious and time-consuming to manually steer this process by trying models one by one. Parallel execution on a cluster is critical for reasonable runtimes. Moreover, since our collaborators often changed the time windows and output semantics for health-related analyses, we had to rerun the whole model selection process over and over several times to get the best accuracy for their evolving task definitions. Finally, reproducible model training is also a key requirement in such scientific settings. All this underscores the importance of automatically scaling deep net model selection on a cluster with high throughput.

System Desiderata. We have the following key desiderata for a deep net model selection system.

1) Scalability. Deep learning often has large training datasets, larger than single-node memory and sometimes even disk. Deep net model selection is also highly compute-intensive. Thus, we desire out-of-the-box scalability to a

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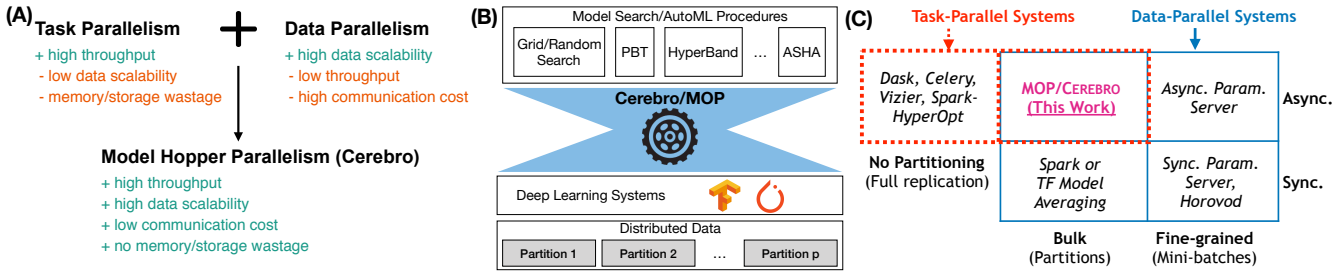


Figure 1: (A) Cerebro combines the advantages of both task- and data-parallelism. (B) System design philosophy and approach of Cerebro/MOP (introduced in [47]): "narrow waist" architecture in which multiple model selection procedures and multiple deep learning tools are supported–unmodified–for specifying/executing deep net computations. MOP is our novel resource-efficient distributed SGD execution approach. (C) Model Hopper Parallelism (MOP) as a hybrid approach of task- and data-parallelism. It is the first known form of *bulk asynchronous* parallelism, filling a major gap in the parallel data systems literature.

cluster with large partitioned datasets (*data scalability*) and distributed execution (*compute scalability*).

2) High Throughput. Regardless of manual grid/random searches or AutoML searches, a key bottleneck for model selection is *throughput*: how many training configurations are evaluated per unit time. Higher throughput enables ML users to iterate through more configurations in bulk, potentially reaching a better accuracy sooner.

3) Overall Resource Efficiency. Deep net training uses variants of mini-batch stochastic gradient descent (SGD) [6, 10, 11]. To improve efficiency, the model selection system has to *avoid wasting resources* and *maximize resource utilization* for executing SGD on a cluster. We have 4 key components of resource efficiency: (1) *per-epoch efficiency*: time to complete an epoch of training; (2) *convergence efficiency*: time to reach a given accuracy metric; (3) *memory/storage efficiency*: amount of memory/storage used by the system; and (4) *communication efficiency*: amount of network bandwidth used by the system. In cloud settings, compute, memory/storage, and network all matter for overall costs because resources are pay-as-you-go; on shared clusters, which are common in academia, wastefully hogging any resource is unethical.

4) Reproducibility. Ad hoc model selection with distributed training is a key reason for the "reproducibility crisis" in deep learning [61]. While some Web giants may not care about unreproducibility for some use cases, this is a showstopper issue for many enterprises due to auditing, regulations, and/or other legal reasons. Most domain scientists also inherently value reproducibility.

Limitations of Existing Landscape. We compared existing approaches to see how well they cover the above desiderata. Unfortunately, each approach falls short on some major desiderata, as we summarize next. Figure 3 and Section 2.2 present our analysis in depth.

1) False Dichotomy of Task- and Data-Parallelism. Prior work on model selection systems, primarily from the ML world, almost exclusively focus on the task-parallel setting [30, 39, 40]. This ignores a pervasive approach to scale to large data on clusters: data partitioning (sharding). A disjoint line of work on data-parallel ML systems do consider partitioned data but focus on training one model at a time, not model selection workloads [41, 57]. Model selection on partitioned datasets is important because parallel file systems (e.g., HDFS for Spark), parallel RDBMSs, and "data lakes" typically store large datasets in that manner.

2) Resource Inefficiencies. Due to the false dichotomy, naively combining the above mentioned approaches could cause overheads and resource wastage (Section 2 explains more). For instance, using task-parallelism on HDFS requires extra data movement and potential caching, substantially wasting network and memory/storage resources. An alternative is remote data storage (e.g., S3) and reading repeatedly at every iteration of SGD. But this leads to orders of magnitude higher network costs by flooding the network with lots of redundant data reads. On the other hand, data-parallel systems that train one model at a time (e.g., Horovod [57] and Parameter Servers [41]) incur high communication costs, leading to high runtimes.

Overall, we see a major gap between task- and data-parallel systems today, which leads to substantially lower *overall resource efficiency, i.e., when compute, memory/storage, and network are considered holistically.*

Our Proposed System. We present CEREBRO, a new system for deep learning model selection that mitigates the above issues with both task- and data-parallel execution. As Figure 1(A) shows, CEREBRO combines the advantages of both task- and data-parallelism, while avoiding the limitations of each. It raises model selection throughput without raising resource costs. Our target setting is *small clusters* (say, tens of nodes), which covers a vast majority (over 90%) of parallel ML workloads in practice [54]. We focus on the common setting of partitioned data on such clusters. Figure 1(B) shows the system design philosophy of CEREBRO: a narrow-waist architecture inspired by [38] to support multiple AutoML procedures and deep net frameworks.

Summary of Our Techniques. At the heart of CEREBRO is a simple but novel hybrid of task- and data-parallelism we call *model hopper parallelism* (MOP) that fulfills all of our desiderata. MOP is based on our insight about a formal optimization theoretic property of SGD: *robustness to the random ordering of the data.* Figure 1(C) positions MOP against prior approaches: it is the first known form of "Bulk Asynchronous" parallelism, a hybridization of the Bulk Synchronous parallelism common in the database world and task-parallelism common in the ML world. As

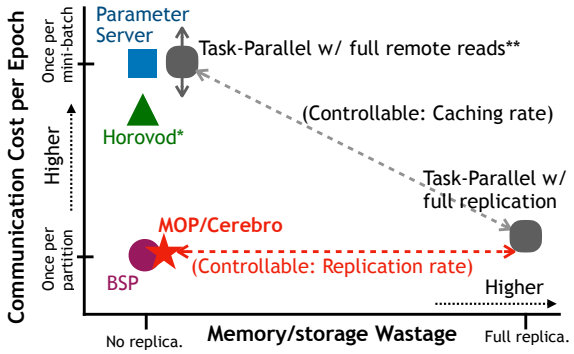


Figure 2: Conceptual comparison of MOP/Cerebro with prior art on two key axes of resource efficiency: communication cost per epoch and memory/storage wastage. Dashed line means that approach has a controllable parameter. *Horovod uses a more efficient communication mechanism than Parameter Server (PS), leading to a relatively lower communication cost. **Task-Parallelism with full remote reads has varying communication costs (higher or lower than PS) based on dataset size.

Figure 2 shows, MOP has the network and memory/storage efficiency of BSP but offers much better ML convergence behavior. Prior work has shown that the BSP approach for distributed SGD (also called "model averaging") has poor convergence behavior [19]. Overall, *considering all resources holistically–compute, memory/storage, and network–MOP can be the resource-optimal choice* in our target setting.

With MOP as its basis, CEREBRO devises an *optimizing scheduler* to efficiently execute deep net model selection on small clusters. We formalize our scheduling problem as a mixed integer linear program (MILP). We compare alternate candidate algorithms with simulations and find that a simple randomized algorithm has surprisingly good performance on all aspects (Section 5). We then extend our scheduler to support replication of partitions, fault tolerance, and elasticity out of the box (Sections 5.5 and 5.6). Such systems-level features are crucial for deep net model selection workloads, which can often run for days. We also weigh a hybrid of CEREBRO with Horovod for model selection workloads with low degrees of parallelism.

Overall, this paper makes the following contributions:

- We present a new parallel SGD execution approach we call *model hopper parallelism* (MOP) that satisfies all the desiderata listed earlier by exploiting a formal property of SGD. MOP is applicable to *any* ML models trained with SGD. We focus primarily on deep nets due to their growing popularity combined with the pressing issue of their resource-intensiveness.
- We build CEREBRO, a general and extensible deep net model selection system using MOP. CEREBRO can support arbitrary deep nets and data types, as well as multiple deep learning tools and AutoML procedures. We integrate it with TensorFlow and PyTorch.
- We formalize the scheduling problem of CEREBRO and compare 3 alternatives (MILP solver, approximate, and randomized) using simulations. We find that a randomized scheduler works well in our setting.
- We extend CEREBRO to exploit partial data replication and also support fault tolerance and elasticity.
- We perform extensive experiments on real model selection workloads with two large benchmark ML datasets: *ImageNet* and *Criteo*. CEREBRO offers 3x to 10x runtime gains over purely data-parallel systems and up to 8x memory/storage gains over purely task-parallel systems. CEREBRO also exhibits linear speedup behavior.

2. BACKGROUND AND TRADEOFFS

We briefly explain mini-batch SGD, the method used for training deep nets. We then compare existing approaches for parallel deep net training and their tradeoffs.

2.1 Deep Net Training with Mini-batch SGD

Deep net training is a non-convex optimization problem [24]. It is solved by mini-batch SGD or its variants (e.g., Adam [34] and RMSprop [17]). SGD is an iterative process that performs multiple passes over the data. Each pass is called an *epoch*. In an epoch, it randomly samples a batch of examples without replacement–called a *mini-batch*–and uses that to estimate the gradient and make a model update. Large datasets have 1000s to millions of mini-batches; so, an epoch makes as many model updates. SGD is inherently sequential; deviating from sequential execution may lead to poor convergence behavior, typically raising the number of epochs needed for a given accuracy. We refer the interested reader to [6, 10] for more technical details on SGD.

2.2 Systems for Distributed Deep Net Training

Most deep learning tools (e.g., TensorFlow) focus on the latency of training *one model at a time*, not on throughput. A popular way to raise throughput is *parallelism*. Thus, various multi-node parallel execution approaches have been studied. All of them fall short on some desiderata, as Figure 3 shows. We group these approaches into 4 categories:

Embarrassingly Task Parallel. Tools such as Python Dask, Celery, Vizier [22], and Ray [45] can run different training configurations on different workers in a task-parallel manner. Each worker can use logically sequential SGD, which yields the best convergence efficiency. This is also reproducible. There is no communication across workers during training, but the whole dataset must be copied to each worker, which does not scale to large partitioned datasets. Copying datasets to all workers is also *highly wasteful of resources*, both memory and storage, which raises costs. Alternatively, one can use remote storage (e.g., S3) and read data remotely every epoch. But such repeated reads wastefully flood the network with orders of magnitude extra redundant data, e.g., see a realistic cost calculation in Table 2..

Bulk Synchronous Parallel (BSP). BSP systems such as Spark and TensorFlow with model averaging [1] parallelize one model at a time. They partition the dataset across workers, yielding high memory/storage efficiency. They broadcast a model, train models independently on each worker's partition, collect all models on the master, average the weights (or gradients), and repeat this every epoch. Alas, this approach converges poorly for highly non-convex models; so, it is almost never used for deep net training [59].

Centralized Fine-grained. These systems also parallelize one model at a time on partitioned data but at the finer

Desiderata	Embarrassing Task Parallelism (e.g., Dask, Celery, Vizier)	Data Parallelism			Model Hopper Parallelism (Our Work)
		Bulk Synchronous (e.g., Spark, Greenplum)	Centralized Fine-grained (e.g., Async Parameter Server)	Decentralized Fine-grained (e.g., Horovod)	
Data Scalability	✗ No (Full Replication) Wasteful (Remote Reads)	✓ Yes	✓ Yes	✓ Yes	✓ Yes
Per-Epoch Efficiency	✓ High	✓ High	✗✗ Lowest	✗ Low	✓ High
SGD Convergence Efficiency	✓✓ Highest	✗✗ Lowest	⟷ Medium	✓ High	✓✓ Highest
Memory/Storage Efficiency	✗✗ Lowest	✓ High	✓ High	✓ High	✓ High
Reproducibility	✓ Yes	✓ Yes	✗ No	✓ Yes	✓ Yes

Figure 3: Qualitative comparisons of existing systems on key desiderata for a model selection system.

Table 1: Notation used in Section 3

Symbol	Description
S	Set of training configurations
p	Number of data partitions/workers
k	Number of epochs for S to be trained
m	Model size (uniform for exposition sake)
b	Mini-batch size
D	Training dataset ($\langle D \rangle$: dataset size, $\|D\|$: number of examples)

granularity of each mini-batch. The most prominent example is Parameter Server (PS) [41]. PS is a set of systems for data-parallel ML. A typical PS consists of *servers* and *workers*; servers maintain the globally shared model weights, while workers compute SGD gradients on a locally stored data partition. Workers communicate with servers periodically to update and retrieve model weights. Based on the nature of these communications, PS has two variants: *synchronous* and *asynchronous*. Asynchronous PS is highly scalable but unreproducible; it often has poorer convergence than synchronous PS due to stale updates but synchronous PS has higher overhead for synchronization.

All PS-style approaches have *high communication* due to their centralized all-to-one communications, which is proportional to the number of mini-batches and orders of magnitude higher than BSP, e.g., 1000x in Table 2.

Decentralized Fine-grained. The best example is Horovod [57]. It adopts HPC-style techniques to enable synchronous all-reduce SGD. While this approach is bandwidth optimal, communication latency is still proportional to the number of workers, and the synchronization barrier can become a bottleneck. The total communication overhead is also proportional to the number of mini-batches and orders of magnitude higher than BSP, e.g., 500x in Table 2.

3. MODEL HOPPER PARALLELISM

We first explain how MOP works and its properties. Table 1 presents some notation. We also theoretically compare the communication costs of MOP and prior approaches.

3.1 Basic Idea of MOP

We are given a set S of training configurations ("configs" for short). For simplicity of exposition, assume for now each runs for k epochs–we relax this later[1]. Shuffle the dataset once and split into p partitions, with each partition located on one of p worker machines. Given these inputs, MOP works as follows. Pick p configs from S and assign one per worker (Section 5 explains how we pick the subset). On each worker, the assigned config is trained on the local partition for a single *sub-epoch*, which we also call a *training unit*. Completing a training unit puts that worker back to the idle state. An idle worker is then assigned a new config that has not already been trained and also not being currently trained on another worker. Overall, a model "hops" from one worker to another after a sub-epoch. Repeat this process until all configs are trained on all partitions, completing one epoch for each model. Repeat this every epoch until all configs in S are trained for k epochs. The invariants of MOP can be summarized as follows:

- *Completeness:* In a single epoch, each training config is trained on all workers exactly once.
- *Model training isolation:* Two training units of the same config are not run simultaneously.
- *Worker/partition exclusive access:* A worker executes only one training unit at a time.
- *Non-preemptive execution:* An individual training unit is run without preemption once started.

Insights Underpinning MOP. MOP exploits a formal property of SGD: *any random ordering* of examples suffices for convergence [6, 10]. Each of the p configs visits the data partitions in a different (pseudorandom) yet in sequential order. Thus, MOP offers high accuracy for all models, comparable to sequential SGD. While SGD's robustness has been exploited before in ML systems, e.g., in Parameter Server [41], MOP exploits it at the *partition level* instead of at the mini-batch level to reduce communication costs. This is possible because we connect this property with model selection workloads instead of training one model at a time.

Positioning MOP. As Figure 1(C) shows, MOP is a new hybrid of task- and data-parallelism that is a form of "bulk asynchronous" parallelism. Like task-parallelism, MOP trains many configs in parallel but like BSP, it runs on partitions. So, MOP is more fine-grained than task parallelism but more coarse-grained than BSP. MOP has no global synchronization barrier within an epoch. Later in

[1]Section 4.2 (Supporting Multiple AutoML Procedures) explains further how CEREBRO can support different configs being trained for different numbers of epochs.

Table 2: Communication cost analysis of MOP and other approaches. *Full replication. †Remote reads. ‡Parameters for the example: $k = 20$, $|S| = 20$, $p = 10$, $m = 1\text{GB}$, $\langle D \rangle = 1\text{TB}$, and $|D|/b = 100\text{K}$.

	Comm. Cost	Example‡
Model Hopper Parallelism	$kmp\|S\| + m\|S\|$	4 TB
Task Parallelism (FR*)	$p\langle D \rangle + m\|S\|$	10 TB
Task Parallelism (RR†)	$k\|S\|\langle D \rangle + m\|S\|$	400 TB
Bulk Synchronous Parallelism	$2kmp\|S\|$	8 TB
Centralized Fine-grained	$2kmp\|S\|\left\lceil \frac{\|D\|}{bp} \right\rceil$	80 PB
Decentralized Fine-grained	$kmp\|S\|\left\lceil \frac{\|D\|}{bp} \right\rceil$	40 PB

Section 5, we dive into how CEREBRO uses MOP to schedule S efficiently and in a general way. Overall, while the core idea of MOP is simple–perhaps even obvious in hindsight–it has hitherto not been exploited in its full generality in ML systems.

Reproducibility. MOP does not restrict the visit ordering. So, reproducibility is trivial in MOP: log the worker visit order for each configuration per epoch and replay with this order. Crucially, this logging incurs very negligible overhead because a model hops only *once per partition*, not for every mini-batch, at each epoch.

3.2 Communication Cost Analysis

We summarize the communication costs of MOP and other approaches in Table 2. It also illustrates the communication costs in bytes for a realistic example based on our case study in Section 1. MOP reaches the theoretical minimum cost of $kmp|S|$. Crucially, note that this cost does not depend on batch size, which underpins MOP's higher efficiency. BSP also has the same asymptotic cost but unlike MOP, BSP typically converges poorly for deep nets and lacks sequential-equivalence. Fine-grained approaches like PS and Horovod have communication costs proportional to the number of mini-batches, which can be orders of magnitude higher. In our setting, p is under low 10s, but the number of mini-batches can even be 1000s to millions based on the batch size.

4. SYSTEM OVERVIEW

We present an overview of CEREBRO, an ML system that uses MOP to execute deep net model selection workloads.

4.1 User-facing API

The CEREBRO API allows users to do 2 things: (1) register workers and data; and (2) launch a deep net model selection workload and get the results. Workers are registered by their IP addresses. For registering a dataset, CEREBRO expects the list of data partitions and their availability on each worker. We assume shuffling and data partitioning across workers is already handled by other means, since distributed data shuffling is well studied. This common data ETL step is also orthogonal to our focus and is not a major part of the total runtime for iterative deep net training.

CEREBRO takes the reference to the dataset, set of initial training configs, the AutoML procedure, and 3 user-defined functions: $input\_fn$, $model\_fn$, and $train\_fn$. It

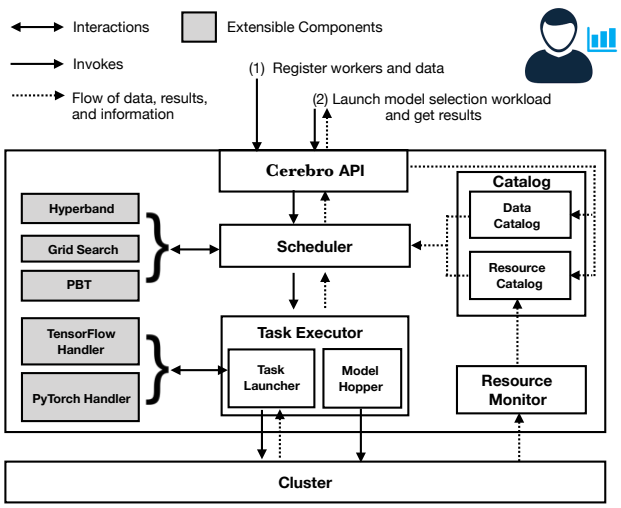


Figure 4: System architecture of Cerebro.

first invokes $input\_fn$ to read and pre-process the data. It then invokes $model\_fn$ to instantiate the neural architecture and potentially *restore* the model state from a previous *checkpointed* state. The $train\_fn$ is invoked to perform one sub-epoch of training. We assume validation data is also partitioned and use the same infrastructure for evaluation. During evaluation, CEREBRO marks model parameters as non-trainable before invoking $train\_fn$. We also support higher-level API methods for AutoML procedures that resemble the popular APIs of Keras [53]. Note that $model\_fn$ is highly general, i.e., CEREBRO supports *all* neural computational graphs on all data types supported by the underlying deep learning tool, including CNNs, RNNs, transformers, etc. on structured data, text, images, video, etc. Due to space constraints, more details of our APIs, including full method signatures and a fleshed out example of how to use CEREBRO are provided in the appendix of our technical report [48].

4.2 System Architecture

We adopt an extensible architecture, as Figure 4 shows. This allows us to easily support multiple deep learning tools and AutoML procedures. There are 5 main components: (1) API, (2) Scheduler, (3) Task Executor, (4) Catalog, and (5) Resource Monitor. Scheduler is responsible for orchestrating the entire workload. It relies on worker and data availability information from the Catalog. Task Executor launches training units on the cluster and also handles model hops. Resource Monitor is responsible for detecting worker failures and updating the Resource Catalog. Section 5 explains how the Scheduler works and how we achieve fault tolerance and elasticity. Next, we describe how CEREBRO's architecture enables high system generality.

Supporting Multiple Deep Learning Tools. The functions $input\_fn$, $model\_fn$, and $train\_fn$ are written by users in the deep learning tool's APIs. We currently support TensorFlow and PyTorch (it is simple to add support for more). To support multiple such tools, we adopt a handler-based architecture to delineate tool-specific aspects: model training, checkpointing and restoring. Note that checkpointing and restoring is how CEREBRO realizes model hops. Task Executor automatically injects the tool-specific aspects from

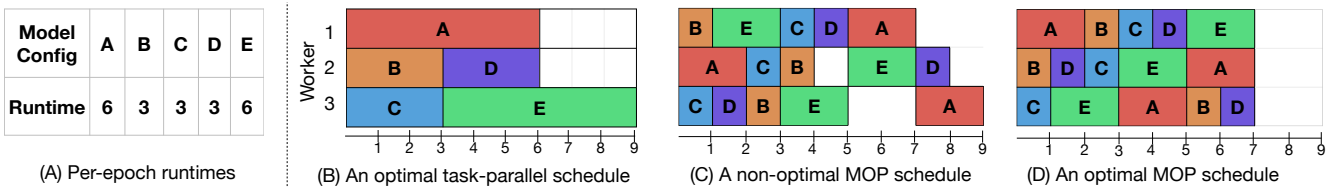


Figure 5: Gantt charts of task-parallel and MOP schedules for a sample model selection workload.

the corresponding tool's handler and runs these functions on the workers. Overall, CEREBRO's architecture is highly general and supports virtually all forms of data types, deep net architectures, loss functions, and SGD-based optimizers.

Supporting Multiple AutoML Procedures Meta-heuristics called AutoML procedures are common for exploring training configs. We now make a key observation about such procedures that underpins our Scheduler. Most AutoML procedures fit a *common template*: create an initial set of configs (S) and evaluate them after each epoch (or every few epochs). Based on the evaluations, terminate some configurations (e.g., as in Hyperband [39] and PBT [30]) or add new configurations (e.g., as in PBT). Grid/random search is a one-shot instance of this template. Thus, we adopt this template for our Scheduler. Given S, CEREBRO trains all models in S for one epoch and passes control back to the corresponding AutoML procedure for convergence/termination/addition evaluations. CEREBRO then gets a potentially modified set S' for the next epoch. This approach also lets CEREBRO support data re-shuffling after each epoch. But the default (and common practice) is to shuffle only once upfront. Grid/random search (perhaps the most popular in practice), Hyperband, and PBT (and more procedures) conform to this common template and are currently supported.

ASHA [40] and Hyperopt [5] are two notable exceptions to the above template, since they do not have a global synchronized evaluation of training configs after an epoch and are somewhat tied to task-parallel execution. While MOP/CEREBRO cannot ensure logically same execution as ASHA or HyperOpt on task-parallelism, it is still possible to emulate them on MOP/CEREBRO without any modifications to our system. In fact, our experiments with ASHA show that ASHA on CEREBRO has comparable–even slightly better!–convergence behavior than ASHA on pure task-parallelism (Section 6.3).

4.3 System Implementation Details

We prototype CEREBRO in Python using XML-RPC client-server package. Scheduler runs on the client. Each worker runs a single service. Scheduling follows a push-based model–Scheduler assigns tasks and periodically checks the responses from the workers. We use a shared network file system (NFS) as the central repository for models. Model hopping is realized implicitly by workers writing models to and reading models from this shared file system. Technically, this doubles the communication cost of MOP to $2kmp|S|$, still a negligible overhead. Using NFS greatly reduces engineering complexity to implement model hops.

5. CEREBRO SCHEDULER

Scheduling training units on workers properly is critical because pathological orderings can under-utilize resources substantially, especially when deep net architectures and/or workers are heterogeneous. Consider the model selection workload shown in Figure 5(A). Assume workers are homogeneous and there is no data replication. For one epoch of training, Figure 5(B) shows an optimal task-parallel schedule for this workload with a 9-unit makespan. Figure 5(C) shows a non-optimal MOP schedulewith also 9 units makespan. But as Figure 5(D) shows, an optimal MOP schedule has a makespan of only 7 units. Overall, we see that MOP's training unit-based scheduling offers more flexibility to raise resource utilization. Next, we formally define the MOP-based scheduling problem and explain how we design our Scheduler.

Table 3: Additional notation used in the MOP MILP formulation

Symbol	Description
$T \in \mathbb{R}^{\lvert S\rvert \times p}$	$T_{i,j}$ is the runtime of unit $s_{i,j}$ (i^{th} configuration on j^{th} worker)
C	Makespan of the workload
$X \in \mathbb{R}^{\lvert S\rvert \times p}$	$X_{i,j}$ is the start time of the execution of i^{th} configuration on j^{th} partition/worker
$Y \in \{0,1\}^{\lvert S\rvert \times p \times p}$	$Y_{i,j,j'} = 1 \iff X_{i,j} < X_{i,j'}$
$Z \in \{0,1\}^{\lvert S\rvert \times \lvert S\rvert \times p}$	$Z_{i,i',j} = 1 \iff X_{i,j} < X_{i',j}$
V	Very large value (Default: sum of training unit runtimes)

5.1 Formal Problem Statement as MILP

Suppose the runtimes of each training unit, aka *unit times*, are given. These can be obtained with, say, a pilot run for a few mini-batches and then extrapolating (this overhead will be marginal). For starters, assume each of the p data partitions is assigned to only one worker. The objective and constraints of the MOP-based scheduling problem is as follows. Table 3 lists the additional notation used here.

$$\texttt{Objective:} \quad \min_{C,X,Y,Z} C \tag{1}$$

$$\begin{aligned}
&\texttt{Constraints:}\\
&\forall i, i' \in [1,\ldots,|S|]\ \forall j, j' \in [1,\ldots,p]\\
&(a)\ X_{i,j} \geq X_{i,j'} + T_{i,j'} - V \cdot Y_{i,j,j'}\\
&(b)\ X_{i,j'} \geq X_{i,j} + T_{i,j} - V \cdot (1 - Y_{i,j,j'})\\
&(c)\ X_{i,j} \geq X_{i',j} + T_{i',j} - V \cdot Z_{i,i',j}\\
&(d)\ X_{i',j} \geq X_{i,j} + T_{i,j} - V \cdot (1 - Z_{i,i',j})\\
&(e)\ X_{i,j} \geq 0\\
&(f)\ C \geq X_{i,j} + T_{i,j}
\end{aligned} \tag{2}$$

We need to minimize makespan C, subject to the constraints on C, unit start times X, model training isolation

matrix Y, and worker/partition exclusive access matrix Z. The constraints enforce some of the invariants of MOP listed in Section 3. Equations 2.a and 2.b ensure model training isolation. Equations 2.c and 2.d ensure worker exclusive access. Equation 2.e ensures that training unit start times are non-negative and Equation 2.f ensures that C captures the time taken to complete all training units.

Given the above, a straightforward approach to scheduling is to use an MILP solver like Gurobi [26]. The start times X then yield the actual schedule. But our problem is essentially an instance of the classical open-shop scheduling problem, which is known to be `NP-Hard` [23]. Since $|S|$ can even be 100s, MILP solvers may be too slow (more in Section 5.4); thus, we explore alternative approaches.

5.2 Approximate Algorithm-based Scheduler

For many special cases, there are algorithms with good approximation guarantees that can even be optimal under some conditions. One such algorithm is "vector rearrangement" [20, 63]. It produces an optimal solution when $|S| \gg p$, which is possible in our setting.

The vector rearrangement based method depends on two values: L_{max} (see Equation 3), the maximum load on any worker; and T_{max} (see Equation 4), the maximum unit time of any training configuration in S.

$$L_{max} = \max_{j \in [1,\ldots,p]} \sum_{i=1}^{|S|} T_{i,j} \tag{3}$$

$$T_{max} = \max_{i \in [1,\ldots,|S|], j \in [1,\ldots,p]} T_{i,j} \tag{4}$$

If $L_{max} \geq (p^2 + p - 1) \cdot T_{max}$, then this algorithm's output is optimal. When there are lot of training configurations, the chance of the above constraint being satisfied is high, yielding us an optimal schedule. But if the condition is not met, the schedule produced yields a makespan $C \leq C^* + (p-1) \cdot T_{max}$, where C^* is the optimal makespan value. This algorithm scales to large $|S|$ and p because it runs in polynomial time in contrast to the MILP solver. For more details on this algorithm, we refer the interested reader to [20, 63].

5.3 Randomized Algorithm-based Scheduler

The approximate algorithm is complex to implement in some cases, and its optimality condition may be violated often. Thus, we now consider a much simpler scheduler based on *randomization*. This approach is simple to implement and offer much more flexibility (explained more later). Algorithm 1 presents our randomized scheduler.

Given S, create $Q = \{s_{i,j} : \forall i \in [1, ..., |S|], j \in [1, .., p]\}$, the set of all training units. Note that $s_{i,j}$ is the training unit of configuration i on worker j. Initialize the state of all models and workers to idle state. Then find an idle worker and schedule a random training unit from Q on it. This training unit must be such that its configuration is not scheduled on another worker and it corresponds to the data partition placed on that worker (Line 10). Then remove the chosen training unit from Q. Continue this process until no worker is idle and eventually, until Q is empty. After a worker completes training unit $s_{i,j}$ mark its model i and worker j as idle again as per Algorithm 2.

5.4 Comparing Different Scheduling Methods

We use simulations to compare the efficiency and makespans yielded by the three alternative schedulers. The

Algorithm 1 Randomized Scheduling

```
1: Input: S
2: Q = {s_{i,j} : ∀i ∈ [1,...,|S|], ∀j ∈ [1,...,p]}
3: worker_idle ← [true,...,true]
4: model_idle ← [true,...,true]
5: while not empty(Q) do
6:   for j ∈ [1,...,p] do
7:     if worker_idle[j] then
8:       Q ← shuffle(Q)
9:       for s_{i,j'} ∈ Q do
10:        if model_idle[i] and j' = j then
11:          Execute s_{i,j'} on worker j
12:          model_idle[i] ← false
13:          worker_idle[j] ← false
14:          remove(Q, s_{i,j'})
15:          break
16:  wait WAIT_TIME
```

Algorithm 2 When $s_{i,j}$ finishes on worker j

```
1: model_idle[i] ← true
2: worker_idle[j] ← true
```

MILP and approximate algorithm are implemented using Gurobi. We set a maximum optimization time of 5min for tractability of experimentation. We compare the scheduling methods on 3 dimensions: 1) number of training configs (two values: 16 and 256), 2) number of workers (two values: 8 and 16), 3) homogeneity/heterogeneity of training configs and workers.

Sub-epoch training time (unit time) of a training config is directly proportional to the compute cost of the config and inversely proportional to compute capacity of the worker. For the homogeneous setting, we initialize all training config compute costs to be the same and also all worker compute capacities to be the same. For the heterogeneous setting, training config compute costs are randomly sampled (with replacement) from a set of popular deep CNNs (n=35) obtained from [2]. The costs vary from 360 MFLOPS to 21000 MFLOPS with a mean of 5939 MFLOPS and standard deviation of 5671 MFLOPS. Due to space constraints we provide these computational costs in the Appendix of our technical report [48]. For worker compute capacities, we randomly sample (with replacement) compute capacities from 4 popular Nvidia GPUs: Titan Xp (12.1 TFLOPS/s), K80 (5.6 TFLOPS/s), GTX 1080 (11.3 TFLOPS/s), and P100 (18.7 TFLOPS/s). For each setting, we report the average of 5 runs with different random seeds set to the scheduling algorithms and also the min and max of all 5 runs. All makespans reported are normalized by the randomized scheduler's makespan.

The MILP scheduler sometimes performs poorer than the other two because it has not converged to the optimal in the given time budget. The approximate scheduler performs poorly when both the configs and workers are heterogeneous. It is also slower than the randomized scheduler.

Overall, the randomized approach works surprisingly well on all aspects: near-optimal makespans with minimal variance across runs and very fast scheduling. We believe this interesting superiority of the randomized algorithm against the approximation algorithm is due to some fundamental

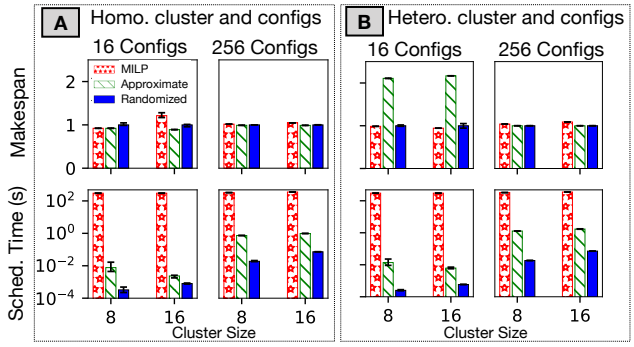


Figure 6: Scheduler runtimes and makespans of the schedules produced in different settings. Makespans are normalized with respect to that of Randomized. (A) Homogeneous cluster and homogeneous training configs. (B) Heterogeneous cluster and heterogeneous training configs.

characteristics of deep net model selection workloads, e.g., large number of configurations and relatively low differences in compute capacities. We leave a thorough theoretical analysis of the randomized algorithm to future work. Based on these results, we use the randomized approach as the default Scheduler in CEREBRO.

5.5 Replica-Aware Scheduling

So far we assumed that a partition is available on only one worker. But some file systems (e.g., HDFS) often replicate data files, say, for reliability sake. We now exploit such replicas for more scheduling flexibility and faster plans.

The replica-aware scheduler requires an additional input: availability information of partitions on workers (an availability map). In replica-aware MOP, a training configuration need *not* visit all workers. This extension goes beyond open shop scheduling, but it is still `NP-Hard` because the open shop problem is a special case of this problem with a replication factor of one. We extended the MILP scheduler but it only got slower. So, we do not use it and skip its details. Modifying the approximate algorithm is also non-trivial because it is tightly coupled to the open shop problem; so, we skip that too. In contrast, the randomized scheduler can be easily extended for replica-aware scheduling. The only change needed to Algorithm 1 is in Line 10: instead of checking $j' = j$, consult the availability map to check if the relevant partition is available on that worker.

5.6 Fault Tolerance and Elasticity

We now explain how we make our randomized scheduler fault tolerant. Instead of just Q, we maintain two data structures Q and Q'. Q' is initialized to be empty. The process in Algorithm 1 continues until both Q and Q' are empty. When a training unit is scheduled, it will be removed from Q as before but now also *added* to Q'. It will be removed from Q' when it successfully completes its training on the assigned worker. But if the worker fails before the training unit finishes, it will be moved back from Q' to Q. If the data partitions present on the failed worker are also available elsewhere, the scheduler will successfully execute the corresponding training units on those workers at a future iteration of the loop in Algorithm 1.

Table 4: Dataset details. All numbers are after preprocessing and sampling of the datasets.

Dataset	On-disk size	Count	Format	Class
ImageNet	250 GB	1.2M	HDF5	1000
Criteo	400 GB	100M	TFRecords	Binary

CEREBRO detects failures via the periodic heart-beat check between the scheduler and workers. Because the trained model states are always checkpointed between training units, they can be recovered and the failed training units can be restarted. Only the very last checkpointed model is needed for the failure recovery and others can be safely deleted for reclaiming storage. The same mechanism can be used to detect availability of new compute resources and support seamless scale-out elasticity in CEREBRO.

5.7 Extension: Horovod Hybrid

Some AutoML procedures (e.g., Hyperband) start with large $|S|$ but then kill some non-promising configs after some epochs. So, only a few configs may train till convergence. This means at the later stages, we may encounter a situation where $|S|$ goes below p. In such cases, CEREBRO can under-utilize the cluster. To overcome this limitation, we explored the possibility of doubly hybridizing MOP with data-parallelism by implementing a hybrid of CEREBRO and Horovod. Just like CEREBRO, Horovod is also equivalent to sequential SGD; so, the hybrid is reproducible. The basic idea is simple: divide the cluster into virtual sub-clusters and run Horovod within each sub-cluster and MOP across sub-clusters. Due to space constraints, we explain this hybrid architecture further in our technical report [48].

6. EXPERIMENTAL EVALUATION

We empirically validate if CEREBRO can improve overall throughput and efficiency of deep net model selection. We then evaluate CEREBRO in depth. Finally, we demonstrate CEREBRO's ability to support multiple AutoML procedures.

Datasets. We use two large benchmark datasets: *ImageNet* [18] and *Criteo* [14]. *ImageNet* is a popular image classification benchmark dataset. We choose the 2012 version and reshape the images to 112×112 pixels[2]. *Criteo* is an ad click classification dataset with numeric and categorical features. It is shipped under sparse representation. We one-hot encode the categorical features and densify the data. Only a 2.5% random sample of the dataset is used[2]. Table 4. summarizes the dataset statistics.

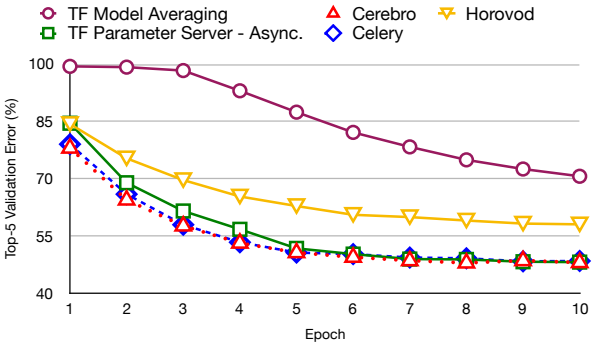
Workloads. For our first end-to-end test, we use two different neural architectures and grid search for hyper-parameters, yielding 16 training configs for each dataset. Table 5 offers the details. We use Adam [34] as our SGD method. To demonstrate generality, we also present results for HyperOpt and ASHA on CEREBRO in Section 6.3.

Experimental Setup. We use two clusters: CPU-only for *Criteo* and GPU-enabled for *ImageNet*, both on CloudLab [55]. Each cluster has 8 worker nodes and 1 master node. Each node in both clusters has two Intel Xeon 10-core 2.20 GHz CPUs, 192GB memory, 1TB HDD and 10

[2]We made this decision only so that all of our experiments can complete in reasonable amount of time. This decision does *not* alter the takeaways from our experiments.

System	ImageNet			Criteo		
	Runtime (hrs)	GPU Utili. (%)	Storage Footprint (GB)	Runtime (hrs)	CPU Utili. (%)	Storage Footprint (GB)
TF PS - Async	19.00	8.6	250	28.80	6.9	400
Horovod	5.42	92.1	250	14.06	16.0	400
TF Model Averaging	1.97	72.1	250	3.84	52.2	400
Celery	1.72	82.4	2000	3.95	53.6	3200
Cerebro	1.77	79.8	250	3.40	51.9	400

(A) Per-epoch makespans and CPU/GPU utilization.



(B) Learning curves of the resp. best configs on *ImageNet*.

Figure 7: End-to-end results on *ImageNet* and *Criteo*. For Celery, we report the runtime corresponding to the lowest makespan schedule. Celery *ImageNet* per-epoch runtime can vary between 1.72-2.02 hours; for *Criteo* between 3.95-5.49 hours. Horovod uses GPU kernels for communication; hence its high GPU utilization.

Table 5: Workloads.*architectures similar to VGG16 and ResNet50, respectively.†serialized sizes.

Dataset	Model arch.	Model size/MB†	Batch size	Learning rate	Regularization	Epochs
ImageNet	{VGG16*, ResNet50*}	VGG16: 792, ResNet50: 293	{32, 256}	$\{10^{-4}, 10^{-6}\}$	$\{10^{-4}, 10^{-6}\}$	10
Criteo	3-layer NN, 1000+500 hidden units	179	{32, 64, 256, 512}	$\{10^{-3}, 10^{-4}\}$	$\{10^{-4}, 10^{-5}\}$	5

Gbps network. Each GPU cluster worker node has an extra Nvidia P100 GPU. All nodes run Ubuntu 16.04. We use TensorFlow v1.12.0 as CEREBRO's underlying deep learning tool. For GPU nodes, we use CUDA version 9.0 and cuDNN version 7.4.2. Both datasets are randomly shuffled and split into 8 equi-sized partitions.

6.1 End-to-End Results

We compare CEREBRO with 5 systems: 4 data-parallel–synchronous and asynchronous TensorFlow Parameter Server (PS), Horovod, BSP-style TensorFlow model averaging–and 1 task-parallel (Celery). For Celery, we replicate the datasets to each worker beforehand and stream them from disk, since they do not fit in memory. I/O time is not an issue for deep nets, where computation vastly dominates I/O; thus, they can be interleaved. We use features available in TensorFlow to achieve this. For all other systems, each worker node has one in-memory data partition. We do not include the time taken to copy data to workers in the end-to-end runtimes. For scheduling, Celery uses a FIFO queue and CEREBRO uses the randomized scheduler. All other systems train models sequentially.

Figure 7 presents the results. We see that CEREBRO significantly improves the efficiency and throughput of model selection. On *ImageNet*, CEREBRO is over 10x faster than asynchronous PS, which has a GPU utilization as low as 9%! Synchronous PS was even slower. CEREBRO is 3x faster than Horovod. Horovod has high GPU utilization because it also includes communication time (Horovod marks the GPU as busy during communication). CEREBRO's runtime is comparable to model averaging, which is as expected. But note that model averaging converges poorly. Celery's runtime is dependent on the scheduling order and thus we report the runtime corresponding to the best schedule. On *ImageNet*, Celery's runtime is comparable to CEREBRO. But note that Celery has a highly bloated 8x memory/storage footprint. Overall, Celery and CEREBRO have the best learning curves, which are almost identical–this is also as expected because MOP ensures sequential equivalence for SGD, just like task-parallelism. Horovod converges slower due to its larger effective mini-batch size.

On *Criteo*, CEREBRO is 14x faster than synchronous PS and 8x faster than asynchronous PS. Both variants of PS report severe CPU under-utilization ($< 7\%$). CEREBRO is also 4x faster than Horovod. CEREBRO's runtime is comparable to model averaging, with about 52% CPU utilization. Celery is somewhat slower than CEREBRO due to a straggler issue caused by the highly heterogeneous model configs for *Criteo*. CEREBRO's MOP approach offers higher flexibility to avoid such straggler issues. A more detailed explanation is given in the appendix of our technical report [48]. All methods have almost indistinguishable convergence behavior on this dataset: all reached 99% accuracy quickly, since the class label is quite skewed.

Overall, CEREBRO is the *most resource-efficient* approach when compute, memory/storage, and network are considered holistically. It also has the *best accuracy behavior*, on par with task-parallelism.

6.2 Drill-down Experiments

Unless specified otherwise, we now show experiments on the GPU cluster, *ImageNet*, and a model selection workload of 8 configs (4 learning rates, 2 regularization values, and ResNet architectures) trained for 5 epochs. Each data partition is placed on only one worker.

Scalability. We study the speedups (strong scaling) of CEREBRO and Horovod as we vary the cluster sizes. Figure 8(A) shows the speedups, defined as the workload completion time on multiple workers vs a single worker. CEREBRO exhibits linear speedups due to MOP's marginal communication costs; in fact, it seems slightly super-linear here because the dataset fits entirely in cluster memory compared to the minor overhead of reading from disk on the single worker. In contrast, Horovod exhibits substantially

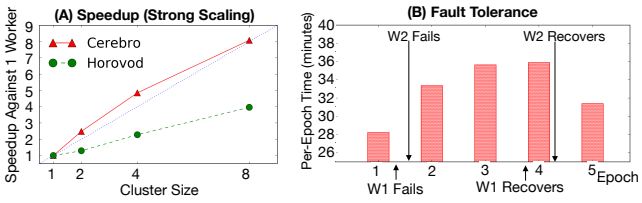


Figure 8: (A) Speedup plot (strong scaling). (B) Fault-tolerance.

sub-linear speedups due to its much higher communication costs with multiple workers.

Fault Tolerance. We repeat our drill-down workload with a replication factor of 3, i.e., each data partition is available on 3 workers. We first inject two node failures and bring the workers back online later. Figure 8(B) shows the time taken for each epoch and the points where the workers failed and returned online. Overall, we see CEREBRO's replica-aware randomized scheduler can seamlessly execute the workload despite worker failures.

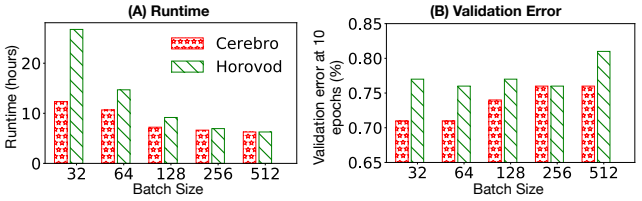


Figure 9: Effect of batch size on communication overheads and convergence efficiency. (A) Runtime against batch size. (B) The lowest validation error after 10 epochs against batch size.

Effect of Batch Size. We now evaluate the effect of training mini-batch size for CEREBRO and Horovod. We try 5 different batch sizes and report makespans and the validation error of the best model for each batch size after 10 epochs. Figure 9 presents the results. With batch size 32, Horovod is 2x slower than CEREBRO. However, as the batch size increases, the difference narrows since the relative communication overhead per epoch decreases. CEREBRO also runs faster with larger batch size due to better hardware utilization. The models converge slower as batch size increases. The best validation error is achieved by CEREBRO with a batch size of 32. With the same setting, Horovod's best validation error is higher than CEREBRO; this is because its effective batch size is 256 (32×8). Horovod's best validation error is closer to CEREBRO's at a batch size of 256. Overall, CEREBRO's efficiency is more stable to the batch size, since models hop per sub-epoch, not per mini-batch.

Network and Storage Efficiency. We study the tradeoff between redundant remote reads (wastes network) vs redundant data copies across workers (wastes memory/storage). Task parallelism forces users to either duplicate the dataset to all workers or store it in a common repository/distributed filesystem and read remotely at each epoch. CEREBRO can avoid both forms of resource wastage. We assume the whole dataset cannot fit on single-node memory. We compare CEREBRO and Celery in the following 2 settings:

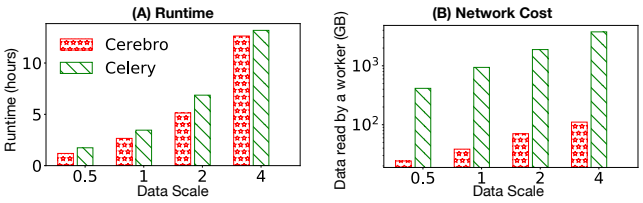


Figure 10: Reading data from remote storage.

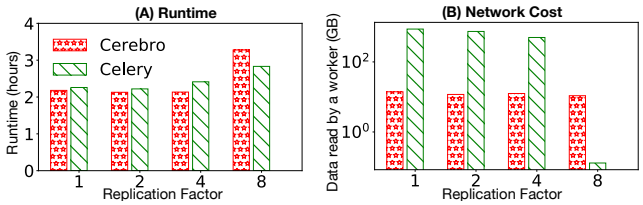


Figure 11: Reading data from distributed storage.

Reading from remote storage (e.g., S3). In this setting, Celery reads data from a remote storage repeatedly each epoch. For CEREBRO each worker keeps one data partition, which is read remotely once and cached in memory. We change the data scale to evaluate effects on the makespan and the number of remote reads per worker. Figure 10 shows the results. Celery takes slightly more time than CEREBRO due to the overhead of remote reads. The most significant advantage of CEREBRO is its network bandwidth cost, which is over 10x lower than Celery's. After the initial read, CEREBRO only communicates models weights during training. In situations where remote reads and networks are not free (e.g., cloud providers), Celery will incur higher monetary costs than CEREBRO. These results show it is perhaps better to partition the dataset on S3, cache partitions on workers on the first read, and then run CEREBRO instead of Celery with full dataset reads from S3 per epoch to avoid copying the whole dataset across workers.

Reading from distributed storage (e.g., HDFS). In this setting, the dataset is partitioned, replicated, and stored on 8 workers. We then load all local data partitions into each worker's memory. Celery performs remote reads for non-local partitions. We vary the replication factor to study its effect on the makespan and the number of remote reads. Figure 10 presents the results. For replication factors 1 (no replication), 2, and 4, CEREBRO incurs 100x less network usage and is slightly faster than Celery. But at a replication factor of 8 (i.e., full replication), CEREBRO is slightly slower due to the overhead of model hops. For the same reason, CEREBRO incurs marginal network usage, while Celery has almost no network usage other than control actions. Note that the higher the replication factor for Celery, the more memory/storage is wasted. CEREBRO offers the best overall resource efficiency–compute, memory/storage, and network put together–for deep net model selection.

Experiments with Horovod Hybrid. Our experiment with the Horovod Hybrid gave an anti-climactic result: the intrinsic network overheads of Horovod meant the hybrid is often slower than regular CEREBRO with some workers being idle! We realized that mitigating this issue requires more careful data repartitioning. We deemed this complexity as perhaps not worth it. Instead, we propose a simpler res-

Table 6: Parameter grid used to randomly sample configuration for Section 6.3.

	Values sampled from
Model	[ResNet18, ResNet34]
Learning rate	$[10^{-5}, \ldots, 10^{-1}]$
Weight decay coefficient	$[10^{-5}, \ldots, 10^{-1}]$
Batch size	$[16, \ldots, 256]$

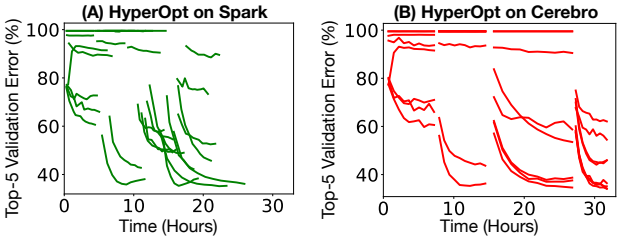


Figure 12: HyperOpt learning curves by time.

olution: if $|S|$ falls below p but above $p/2$, use Cerebro; if $|S|$ falls below $p/2$, just switch to Horovod. This switch incurs no extra overhead. Due to space constraints, we skip the details here and explain this experiment further in our technical report [48].

6.3 Experiments with AutoML Procedures

We experiment with two popular AutoML procedures: HyperOpt [5] and ASHA [40]. For HyperOpt, we compare Cerebro and Spark as the execution backends. Spark is a backend supported natively by HyperOpt; it distributes only the models, i.e., it is task-parallel on fully replicated data. For ASHA, we compare Cerebro and Celery as the execution backends. We use *ImageNet*, GPU cluster, and PyTorch. Training configs are sampled from the grid shown in Table 6. For Cerebro data is partitioned without replication; for Spark and Celery the dataset is fully replicated.

Both HyperOpt and ASHA keep exploring different configs until a resource limit is reached. For HyperOpt, this limit is the maximum number of configs; for ASHA, it is the maximum wall-clock time. During the exploration HyperOpt uses Bayesian sampling to generate new configs; ASHA uses random sampling. For both methods, the generated configs are dependent on the completion order of configs across task-parallel workers. Thus, it is impossible for Cerebro to *exactly* replicate HyperOpt or ASHA ran with task-parallelism. However, we can closely *emulate* HyperOpt and ASHA on Cerebro by making the number of simultaneously trained configs ($|S|$) equal to the number of workers (p) and without making any changes to Cerebro.

HyperOpt. We run an experiment using HyperOpt with a max config budget of 32. We train each config for 10 epochs. With this configuration, HyperOpt on Cerebro (resp. Spark) took 31.8 (resp. 25.9) hours. Figure 12 shows all learning curves. We found that the slightly higher (23%) runtime of Cerebro is mainly due to the lower degree of parallelism ($|S| = 8$). However, this issue can be mitigated by increasing the number of simultaneously trained configs. Although individual configs are not comparable across the two systems, the best errors achieved are close (34.1% on Cerebro; 33.2% on Celery).

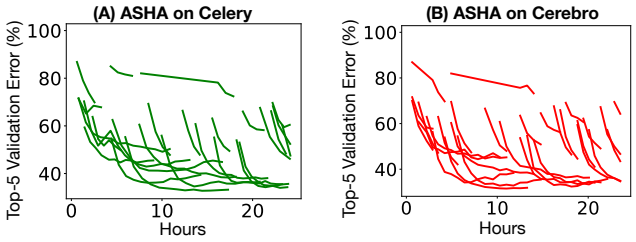


Figure 13: ASHA learning curves by time.

ASHA. We use ASHA with a max epoch budget (R) of 9, a selection fraction (η) of 3, and a time limit of 24hr. With these settings, ASHA trains for a maximum of 13 epochs over 3 stages: 1, 3, and 9 epochs. Only the more promising configurations are trained for more epochs. In the given time limit, ASHA on Cerebro (resp. Celery) explored 83 (resp. 67) configs. Figure 13 shows all learning curves. Like HyperOpt, even though the configs are not directly comparable, the best errors achieved are close (31.9% on Cerebro; 33.2% on Celery). More details about this experiment and experiments with another AutoML procedure (HyperBand) are presented in the appendix of our technical report [48].

7. DISCUSSION AND LIMITATIONS

Integration into Other Systems. MOP's generality makes it amenable to emulation on top of BSP data-parallel systems such as parallel RDBMSs and dataflow systems. Pivotal/VMWare has recently collaborated with us to integrate MOP into Greenplum by extending the MADlib library for running TensorFlow on Greenplum-resident data [44, 60]. Greenplum's customers are interested in this integration for enterprise ML use cases including language processing, image recognition, and fraud detection. We have also integrated Cerebro into Apache Spark [16]. Cerebro's Spark implementation can deploy MOP on existing resource managers such as YARN and Mesos. Alternatively, one can also deploy Cerebro as a standalone application by wrapping it as tasks accepted by the resource manager. We leave such extensions to future work.

Applicability to Other ML Model Families. We focused primarily on deep nets due to their growing popularity, high sensitivity to model configurations, and resource-intensiveness. However, note that MOP and Cerebro's ideas are directly usable for model selection of *any* ML models trainable with SGD. Examples include linear/logistic regression, some support vector machines, low-rank matrix factorization, and conditional random fields. In fact, since linear/logistic regression can be trivially expressed in the deep learning tools's APIs, Cerebro will work out of the box for them. Cerebro's high memory efficiency makes it easier for users to store the entire large datasets in distributed memory, which can significantly reduce runtimes of such I/O-bound ML models. We leave an empirical analysis of these less compute-intensive models to future work.

Model Parallelism and Batching. Cerebro currently does not support model parallelism (for models larger than single-node memory) or model batching (running multiple models on a worker at a time). It is possible to remove these two limitations from Cerebro. For instance, model

parallelism can be supported with the notion of virtual nodes composed of multiple physical nodes that together hold a very large model. Model batching can be supported with multiple virtual nodes mapped to a physical node. We leave these extensions to future work.

8. RELATED WORK

Systems for Model Selection. Google Vizier [22], Ray Tune [43], Dask-Hyperband [56], SparkDL [15], and Spark-Hyperopt [29] are systems for model selection. Vizier, Ray, and Dask-Hyperband are pure task-parallel systems that provide implementations of some AutoML procedures. SparkDL and Spark-Hyperopt use Spark underneath but only for distributing the configs, not the data–they replicate the full dataset to each worker like task-parallelism. CEREBRO offers higher overall resource efficiency compared to this prior landscape of pure task- or pure data-parallelism.

Hybrid Parallelism in ML Systems. MOP is inspired by the classical idea of process migration in OS multiprocessing [3]. We bring this idea to the multi-node data-partitioned regime. This general idea has been applied before in limited contexts in ML systems [7,37]. The closest to our work is [13], which proposes a hybrid scheme for training many homogeneous CNNs for images on a homogeneous GPU cluster. They propose a ring topology to migrate models, resembling a restricted form of MOP. But their strong homogeneity assumptions can cause stalls in general model selection workloads, e.g., due to heterogeneous neural architectures or clusters. In contrast, our work approaches this problem from first principles and formalizes it as an instance of open shop scheduling. This powerful abstraction lets CEREBRO support arbitrary deep nets and data types, as well as heterogeneous neural architectures and clusters. It also lets CEREBRO offer other crucial systems capabilities: replication, fault tolerance, elasticity, and arbitrary AutoML procedures unlike prior work. SystemML also supports a hybrid of task- and data-parallelism for linear algebra-based classical ML [9]. They enable task-parallelism on top of data-parallel MapReduce and focus on better plan generation to exploit multi-cores and clusters. CEREBRO is complementary because we focus on deep nets and SGD's data access pattern, not linear algebra-based classical ML.

AutoML Procedures. AutoML procedures such as Hyperband [39] and PBT [30] are orthogonal to our work and exist at a higher abstraction level. They fit a common template of per-epoch scheduling in CEREBRO. While ASHA [40] does not fit this template, CEREBRO can still emulate it well and offer similar accuracy as pure task-parallelism without any modifications to CEREBRO. Bayesian optimization is another popular line of AutoML metaheuristics in the ML world. Some such techniques have a high degree of parallelism in searching configs (e.g., Hyperopt [5]); CEREBRO supports these variants. Some others perform sequential search, leading to a low degree to parallelism (e.g., [4,35]); these may not be a fit for CEREBRO.

Cluster Scheduling for Deep Learning. Gandiva [64], Tiresias [25], and SLAQ [65] are cluster scheduling frameworks for deep learning. Their focus is on lower-level primitives such as resource allocation and intra-server locality awareness for optimizing the average job completion time. CEREBRO is complementary to them as it operates at a higher abstraction level and targets the throughput of model selection. How compute hardware is allocated is outside our scope. There is a long line of work on general job scheduling algorithms in the operations research and systems literatures [12,21,27]. Our goal is *not* to create new scheduling algorithms but to apply known algorithms to a new ML systems setting based on MOP.

Systems for Distributed SGD. There is much prior work on systems to reduce the latency of distributed SGD. Most of them focus on optimizing centralized fine-grained SGD (e.g., [28,32,52,66]) and/or decentralized fine-grained SGD (e.g., [42,52,62]). Such systems are complementary to our work as they improve parallelism for training a single model at a time, while our focus is on model selection. As we showed, such systems have higher communication complexity (and thus, higher runtimes) than MOP in our setting. Also, since CEREBRO performs logically sequential SGD, it ensures theoretically best convergence efficiency. CROSSBOW [36] proposes a novel variant of model averaging for single-server multi-GPU environment to overcome the convergence issues of naive model averaging. But it too is complementary to our work, since it too focuses on training one model at a time. Overall, our work breaks the dichotomy between such data-parallel approaches and task-parallel approaches, thus offering better overall resource efficiency.

System Optimizations. Several works study optimizing deep learning tools' internals, including better pipelining of computation and communication [49], better compilation techniques [8,31], and model batching [50]. Vista [46] stages computations and optimizes memory use for transfer learning from CNNs. All these ideas are complementary to CEREBRO, since they optimize lower level issues. MOP is general enough to allow CEREBRO to be hybridized with such ideas.

9. CONCLUSIONS AND FUTURE WORK

Simplicity that still achieves maximal functionality and efficiency is a paragon of virtue in real-world systems. We present a simple but novel and highly general form of parallel SGD execution, MOP, that raises the resource efficiency of deep net model selection without sacrificing accuracy or reproducibility. MOP is also simple to implement, which we demonstrate by building CEREBRO, a fault-tolerant deep net model selection system that supports multiple popular deep learning tools and model selection procedures. Experiments with large ML benchmark datasets confirm the benefits of CEREBRO. As for future work, we plan to hybridize MOP with model parallelism and batching and also support more complex model selection scenarios such as transfer learning.

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