Tech Report of Distributed Deep Learning on Data Systems: A Comparative Analysis of Approaches

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ABSTRACT

Deep learning (DL) is growing in popularity for many data analytics applications, including among enterprises. Large business-critical datasets in such settings typically reside in RDBMSs or other data systems. The DB community has long aimed to bring machine learning (ML) to DBMS-resident data. Given past lessons from in-DBMS ML and recent advances in scalable DL systems, DBMS and cloud vendors are increasingly interested in adding more DL support for DB-resident data. In this paper, we show that there is no single "best" approach to achieve that goal and an interesting tradeoff space of approaches exists. We explain four canonical approaches, compare them analytically on multiple criteria (e.g., runtime efficiency and ease of governance) and compare them empirically with large-scale DL workloads. Our experiments and analyses show that it is non-trivial to meet all practical desiderata well and there is a Pareto frontier; for instance, some approaches are 3x-6x faster but fare worse on governance and portability. Our results and insights can help DBMS and cloud vendors design better DL support for DB users. All of our source code, data, and other artifacts are available at https://github.com/makemebitter/cerebro-ds.

1 INTRODUCTION

Deep learning (DL) for data analytics continues to grow in popularity, leading to a growing demand for products that make it easier to adopt DL, especially among enterprises [54]. The DBMS community has long worked on bringing machine learning (ML) closer to the home of business-critical datasets in enterprises: DBMSs and other data systems. This paradigm of "In-DBMS ML" (or "In-data system ML") has waxed and waned over the last 20 years, with 3 general waves of work. It now merits a revisit in the era of DL.

One may wonder if DL is useful for DBMS users, since DL is primarily popular on unstructured data, while DBMSs mainly handle structured data [63]. Although much of DL's successes are on unstructured data that are commonly stored on filesystems or data lakes, DBMSs have long provided storage support for text, multimedia [90, 122], and other objects [21, 109]. Furthermore, due to the benefits of embedding learning and less feature engineering in DL [113, 120], many recent works in both research and enterprise applications show that DL is becoming increasingly usable and effective even on structured data [47, 73, 77, 114, 115]. Multimodal analytics combining structured and unstructured data are also popular and relevant for DB users [18, 75, 83, 118]. Finally, DL's "interpretability" pain, once a showstopper for some enterprise users, is being actively mitigated by ML researchers [30, 126].

1.1 Lessons from In-RDBMS ML

In the first wave of in-RDBMS ML, DB vendors built "data mining tools" that scaled a few ML algorithms to DB-resident data [12, 31, 89]. They enabled access to ML from the SQL console. But as ML algorithms grew in complexity, a second wave of unified implementation abstractions were devised for in-data system ML [32, 43]; MADlib [49] and Spark MLlib [79] are key examples. The third wave is seeing cloud DBMS vendors adding more in-RDBMS ML support, e.g., Google's BigQuery ML [2, 6, 11], as well as invoking DL from DBMSs [2, 7].

In this context, DBMS and cloud vendors are increasingly asking: *"How to enable seamless support for DL over DB-resident data?"*. The past waves of in-RDBMS ML offer at least four lessons.

(1) The main user base of in-RDBMS ML tools are not Python-oriented data scientists but SQL-oriented business analysts. Such users increasingly want access to DL training and inference *from within the SQL console*. As per estimates by the MADlib team, about 20-25% of Greenplum customers today use its in-RDBMS ML analytics capabilities alongside SQL analytics.

(2) Although *governance and provenance* were always important for enterprises, they now have renewed urgency for *all companies* due to new laws such as GDPR [34] and CCPA [87]. Companies will likely start frowning upon DL users manually exporting, copying, and moving business-critical data around in an ad hoc manner. Although one could program to automate such processes and use services like MLFlow and Kubeflow [62, 81], it is still an extra burden for the enterprise users to learn, especially when they are already familiar with established DBMS support for governance/provenance.

(3) It is far too tedious for DBMS developers to reimplement DL algorithms. So, one must *preserve the usability of DL tools* such as TensorFlow for specifying complex DL workloads. This also allows analysts to just reuse DL training specification programs written by data scientists or others.

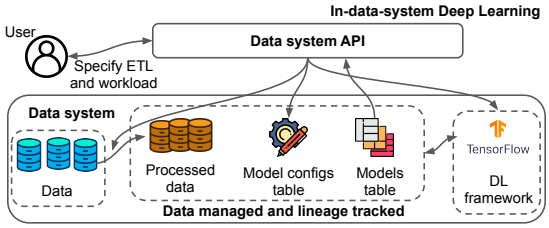

Figure 1: In-data-system DL. Data system invokes DL tool and helps mitigate data provenance/governance issues.

(4) Parallel RDBMSs already offer a mature execution engine on sharded large-scale data. But state-of-the-art distributed DL execution tools such as Horovod [104] are still notoriously painful to set up, operate, and debug [17]. This presents parallel RDBMSs/data systems an opportunity to *bridge the gap on scalable execution.*

Overall, we see two contrasting paradigms for how DL is brought to DB-resident data. The DL user can export the data to a file system, invoke a DL tool manually, and manage all derived data/metadata/artifacts on their own. Alternatively, in the "in-data system DL" approach, the DL workload and ETL are orchestrated by the data system itself, as Figure 1 illustrates. Crucially, this approach leaves room for *implementation flexibility* on how exactly the DL tool consumes the data; this flexibility opens up possibilities that we will explore later.

1.2 Toward In-Data System DL

Apache MADlib has recently pioneered in-DBMS DL support [9]. The DL workload is specified using Keras APIs, enabling business analysts to reuse DL configurations written by, say, data scientists. Under the hood, MADlib ships mini-batch data from the DB to a TensorFlow function invoked in a DBMS UDF/UDAF. TensorFlow performs the forward and backward passes. For distributed execution, MADlib used the "model averaging" (MA)[1] heuristic for SGD [43, 129]. Alas, MA has poor convergence behavior for highly non-convex DL [85]. Thus, this approach is sub-optimal for bringing DL to DBs.

We observe that MA misses a major opportunity for parallelism in DL: *model selection.* ML theory teaches us that tuning hyperparameters is crucial, and this leads to the need for training many models [65, 105]. Often, DL users also compare alternate neural architectures, alter the base features, etc. Thus, model selection in practice often leads to dozens, if not hundreds, of models to train in one go [41, 85].

Exploiting the above observation, recent work proposed a new approach to distributed DL model selection called Model Hopper Parallelism (MOP) [66, 84, 85]. MOP is a *hybrid* of sharded data parallelism and task parallelism, the latter being common in the ML world [100]. MOP works as follows: train different models on different workers in parallel for one *sub-epoch* on their local shards, checkpoint and "hop" the models across workers, and restart training the *same epoch* on the next worker's shard; repeat all this across epochs. MOP is a form of bulk *asynchronous* parallelism since it imposes no barrier synchronization across workers, unlike Bulk Synchronous Parallel (BSP) data systems. Overall, MOP was shown to be the most resource-efficient approach to distributed DL model selection [85].

[1]In addition to MA, MADlib has adopted one of the approaches we will evaluate [10].

1.3 Focus of this Paper

Given the benefits of MOP we ask: *"How to bring MOP-based DL to DB-resident data?"* We find that there is no single "best" approach, and there is an interesting tradeoff space of alternative approaches. This paper explains these approaches, contrasts them analytically, and compares them empirically with large-scale DL workloads. We use Greenplum as the archetype but emphasize that the approaches compared are generic and applicable to any parallel RDBMS. Thus, *our results could be of wide interest to all DBMS and cloud vendors.*

We seek approaches that *do not change the code* of the data system. This eases practical adoption but restricts how MOP can be applied. For instance, Spark now supports flexible scheduling of workers [36]; this made it easy to integrate MOP with Spark in the Cerebro system [1]. But parallel RDBMSs such as Greenplum, AWS Redshift, etc., use BSP across workers, conflicting with MOP's asynchrony. We have *multiple axes of comparative evaluation*, including *runtime efficiency*, *ease of governance*, *implementation difficulty*, and *portability*. Section 3 explains all approaches and Section 4 compares them in detail, but as a preview, Figure 2 shows the approaches on the first two axes.

We compare 4 new approaches: (1) Fully in-DBMS MOP using User-Defined Aggregate Functions (UDAF); this approach has been adopted by MADlib [10] (2) Partially in-DBMS MOP using Concurrent Targeted Queries (CTQ); (3) In-DB but *not* in-DBMS MOP using Direct Access (DA); and (4) Regular out-of-DBMS approach using Cerebro-Spark. MA is largely dominated by the UDAF approach but all the other approaches fall on the Pareto frontier. For instance, the out-of-DBMS Cerebro-Spark approach and in-DB DA approaches are much more efficient than UDAF but may be harder to govern in a production environment. The CTQ approach offers a middle ground on these two axes.

Our comparative analyses of these approaches expose more interesting gaps. For instance, with theoretical and simulation analyses, we show that the efficiency gap between CTQ and UDAF grows wider when the models and hardware are more heterogeneous, even up to 6x in a realistic scenario. Finally, an extensive empirical comparison using the ML benchmark datasets ImageNet and Criteo shows that the real runtime gaps between UDAF and DA be as high as 3x. Overall, our experiments and analyses show that it is beneficial to bring MOP-based DL to DB-resident data, but it is non-trivial to meet all practical desiderata. We hope our results spur more conversations in the DB and cloud industries on how best to support DL on DB-resident data.

In summary, this paper makes the following contributions:

- To the best of our knowledge, this is the first paper to analyze the tradeoffs and design alternatives of supporting large-scale DL model selection on DB-resident data.
- We show a spectrum of possible approaches on the Pareto frontier of efficiency, ease of governance, and other practical desiderata. In particular, we show a new approach that is in-DB but not in-DBMS, posing new accessibility questions for DB vendors.

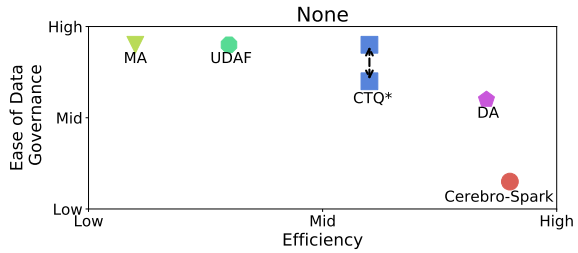

Figure 2: Tradeoffs of ease of data governance vs. efficiency for various approaches. *Depending on an implementation detail CTQ may have the same ease of governance as MA and UDAF; see Section 4.2 for details.

- We perform a formal analysis of the limits of the efficiency gaps between the new approaches.
- We perform an extensive empirical comparison of the approaches using large ML benchmark datasets to evaluate their runtimes, scalability, and internal design tradeoffs.

2 BACKGROUND AND PRELIMINARIES

We start with a brief background on the most common DL training algorithm: mini-batch SGD, and the burden of DL model selection. Then we explain the challenges and constraints faced by in-DBMS DL approaches. Finally, we review and compare various paradigms on how to parallelize DL model building on DBMSs and explain why MOP is perhaps the most desirable choice, given the DBMS constraints.

2.1 Background on ML Concepts

Mini-batch SGD. DL training is a non-convex optimization problem [46]. It is solvable by mini-batch SGD or its variants (e.g., Adam [58] or RMSprop [23]). SGD is iterative in nature and performs multiple passes over the data. Each pass is called an *epoch*. Within one epoch, it randomly samples a batch of examples (called a *mini-batch*) without replacement and uses that to estimate gradients and updates the model. It repeats this process until the epoch ends. Such sampling is achieved in practice by performing a *random shuffle* of the dataset beforehand or after each epoch. In SQL, this can be easily achieved using ORDER BY RANDOM() [43]. SGD is inherently sequential; deviating from sequential execution may worsen convergence behavior [85, 125], typically raising the number of epochs needed for a given accuracy.

Model selection. DL is a complex ML approach that requires subtle tuning. Developing a DL model from scratch is challenging, for the model's performance depends non-linearly on the neural architectures and hyperparameter settings. Neural architecture defines a DL model, and different architectures could offer drastically different accuracies on the same task. Hyperparameters are the knobs that control how the model is trained and regularized. It is critical to tune these settings as they could greatly affect the model accuracy [65, 105]. Hence, the user needs to find the best combination of choices for neural architectures and hyperparameters; this process is called model selection [65]. Due to model selection burdens, DL routinely requires training of dozens to hundreds of models [41]. There is a line of research trying to guide model selection with meta-heuristics like grid/random search, PBT [51], ASHA [70], Hyperopt [24], etc. These works are orthogonal to our work, because they study the algorithmic issue of *what* configurations to explore, while our paper studies the systems-level issue of *how* to execute a given model selection workload efficiently and compares the alternatives on multiple fronts.

2.2 Constraints and Challenges in Bringing DL to DBMSs

It is challenging to implement in-DBMS DL while not modifying the DBMSs, because of constraints that many parallel DBMSs share. We summarize these constraints as follows:

Bulk synchronous parallelism (BSP). Each query executes in an all-or-nothing manner on a dataset that is sharded across workers. A synchronization barrier is injected at the end of every query. There is no easy way to poll partial results from the workers operating on data shards.

No message-passing among workers. The only allowed communication method among workers is the pipes provided by the DBMS. Workers are not allowed to communicate with each other via other methods like MPI or RPC. This constraint would make some distributed DL paradigms especially hard to implement.

One query at a time. For each database connection session, only one query is permitted at any time. Model selection workloads typically issue multiple concurrent queries. This may require spawning multiple processes on the same client and opening multiple connections, which may be considered an anti-pattern.

Data access through DBMS. In a DBMS, data is usually compressed and stored on disk as pagefiles. To access data, one must go through the DBMS query stack. If the data is frequently and iteratively accessed as we see in DL training, such repeated accessing and decompression could bring serious overheads.

2.3 Paradigms for Distributed DL

There has been a lot of work on multi-node parallel DL training. However, most of these techniques do not have or assume a trivial data layer. Adjustments or re-implementation must be made to integrate them into an existing data system. The DBMS has constraints that render many of the approaches unsuitable or difficult to implement. We translate the constraints of Sec 2.2 into the following requirements for distributed DL paradigms for amenability to the in-DBMS setting.:

- **Centralized communication.** As mentioned in Section 2.2, we want the communication pattern to be as simple as possible. P2P communication is typically not allowed.
- **Coarse-grained parallelization.** The training would better be parallelized at epoch instead of mini-batch level. Since we will embed the training jobs as data system tasks/queries, fine-grained parallelization will lead to massive number of queries that can cause heavy overheads.
- **Data-parallelism.** The data is already partitioned in the data system. Fully replicating the entire data across workers is not desirable and may not even be feasible at large scales.
- **Fast convergence.** In order to save computational and resource costs of model selection, we want the models to converge fast in terms of number of epochs, ideally resembling

Table 1: Summary of various parallel paradigms' fitness for in-data-system DL.

	Centralized communication	Coarse grained	Data-parallel	Fast convergence
Task Parallel	✓	✓	✗	✓
Model Avg.	✓	✓	✓	✗
Param. Server	✓	✗	✓	✓
Horovod	✗	✗	✓	✓
MOP	✓	✓	✓	✓

the learning curves obtained by the gold-standard sequential SGD.

Next we explain the major distributed DL model selection approaches in the literature and explain how well they fit (or not) the above constraints. Table 1 summarizes our comparative analysis.

Task Parallel. In this paradigm, different model configs of the model selection workload run on different workers in a task-parallel manner. Example tools include Python Dask, Celery, Vizier [45], and Ray [82]. Workers locally run sequential SGD on the whole dataset. Thus, this approach provides the best convergence efficiency. There is no communication across workers during training. Still, it *requires full data replication on each worker*, which is inefficient, and may not even be feasible for large sharded datasets in DBMSs.

Model Averaging (MA). In BSP systems such as TensorFlow with model averaging [3], data is sharded. The model configs are trained in parallel one-by-one. Every model is broadcasted and trained on each worker's data shard independently. Then a merge step takes place on the master; it averages the weights (or gradients). This process repeats every epoch. This approach is a potential candidate and has been adopted by MADlib [9]. Alas, it converges poorly for DL models, which are highly non-convex [108]. Nevertheless, since it satisfies most of the constraints, we include it as a key baseline in our experiments.

Fine-grained Parallel. These paradigms are similar to BSP, but they work at a finer granularity at the mini-batch level. The communication pattern can be centralized or decentralized. The most prominent example of centralized paradigms is Parameter Server (PS) [71]. The best example for decentralized paradigms is Horovod [104]; it adopts HPC-style techniques to enable synchronous all-reduce SGD. These methods all have good convergence behavior but very high communication costs. They too are not good candidates because of the finer granularity. Horovod further requires P2P communication patterns that are not allowed in most data systems.

Model Hopper Parallelism (MOP). MOP used in system Cerebro [85] is recent progress towards resource-efficient DL. This is a hybrid of task- and data-parallelism. Each worker is assigned one model config from the model selection workload and trains the model with its local data shard; this process is called one sub-epoch. When one sub-epoch finishes, the model is passed to other data shards for further training. After several sub-epochs, every model finally has seen the entire dataset, and that is one epoch of training. Overall, a model *hops* from one worker to another in-between sub-epochs. The scheduling is done via an asynchronous random scheduler that works well on heterogeneous workloads and supports fault tolerance. MOP fits all our requirements because

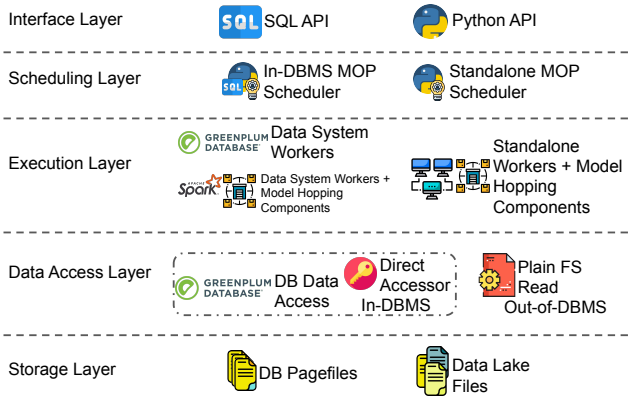

Figure 3: Design alternatives for MOP in DBMS.

communication-wise, it has a centralized pattern and low cost, for it works at sub-epoch granularity. Data-wise, it works nicely with sharded data. Finally, it offers equivalency to sequential SGD, which has the highest convergence efficiency. Hence, we decided MOP would be a better choice for in-DBMS DL.

3 OVERVIEW OF ALTERNATE APPROACHES

Given the benefits of MOP, the question becomes how to bring MOP-based DL to DBMS-resident data. There are multiple possible approaches due to the implementation flexibility. To better explain these alternatives, we first divide the components of MOP execution into five layers of design decisions: Interface, Scheduling, Execution, Data Access, and Storage. Each layer can be implemented in flexible ways. Figure 3 summarizes the architectural alternatives.

(1) **Interface layer**: the first layer is the high-level APIs that take in the user's DL model selection workload; it could be implemented in SQL, familiar to business analysts, or in Python, familiar to data scientists.
(2) **Scheduling layer**: the MOP scheduler orchestrates the execution and manages placements of training units. We could implement the scheduler as an in-DBMS procedure or use a standalone MOP scheduler.
(3) **Execution layer**: the execution engine invokes DL tools and conducts model training/validation via mini-batch SGD. The model hopping components handle the placement of models. We could use the data systems' execution engine or resort to standalone MOP workers for this layer. Model hopping can be cast as SQL queries or be implemented as separate components with other communication methods.
(4) **Data Access and Storage layer**: we could leave the data in DBMS or export them. There are also multiple ways to access the data; if data is in a data lake, access is trivial. Otherwise, if the data is in DBMS, we can rely on DBMS's native data accessor or use a technique we call Direct Access to bypass the whole query stack and access the data from its physical storage directly.

Because of these flexibilities, there are various approaches for the end-to-end implementation of MOP. We find four interesting canonical approaches: (1) Fully in-DBMS MOP using User-Defined Aggregate Functions (UDAF); (2) Partially in-DBMS MOP using Concurrent Targeted Queries (CTQ); (3) In-DB but not in-DBMS MOP

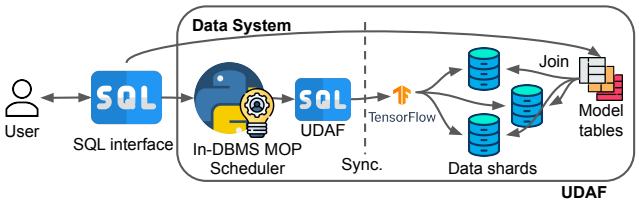

Figure 4: UDAF approach. Fully in-DBMS.

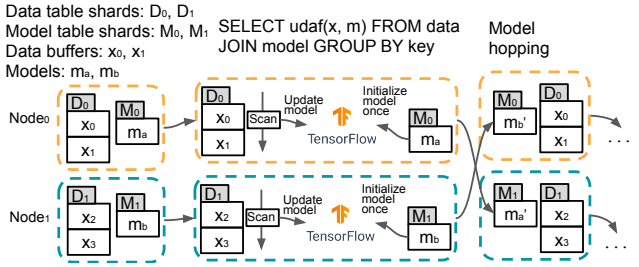

Figure 5: Conceptual illustration of one sub-epoch of UDAF.

using Direct Access (DA); and (4) Regular out-of-data-system approach using Cerebro-Spark. We use Greenplum as the archetype but emphasize that the approaches compared are generic and applicable to any parallel DBMS. We do not claim these are the only possible approaches; rather, we find these are prototypical examples of feasible approaches based on the combinations of design decisions in Figure 3. We now introduce each approach and dive into the analysis and comparisons later in Section 4.

3.1 User-Defined Aggregate Functions (UDAF)

This approach implements MOP as DBMS extensions with UDFs and UDAFs. On the 5 design decisions: it provides an SQL interface, employs an in-DBMS MOP scheduler, uses DBMS as the execution engine, stores data in the DBMS, and accesses the data through the DBMS. This approach is called fully in-DBMS because all functions are in-DBMS procedures, plus both data and models are stored in DBMS.

Figure 4 illustrates the approach. It maintains a data table storing the dataset and a model table storing the DL model selection workload, with each row containing a model. Both tables are sharded based on distribution keys. The DBMS will hash the keys and put rows with the same key to the same shard. By manipulating these keys, we can control the affinity of data/model. The user first defines the model architectures and workloads through a SQL interface. DBMS then invokes the MOP scheduler implemented in UDF.

This approach's scheduler is synchronous due to the BSP nature of in-DBMS execution, in contrast to the asynchronous random scheduler that standalone MOP adopts. It uses a simple round-robin heuristic for placing models on data shards. The scheduler translates the workload into UDAF queries dispatched and executed on the joined table of data and model. These UDAFs subsequently invoke DL tool (we use TensorFlow/Keras) for training. It schedules a batch of sub-epochs on the workers at a time and waits for completion. After several batches, one epoch is completed; it then repeats the process to train for multiple epochs.

Conceptually, each UDAF is a query of `SELECT udaf(...) FROM data JOIN model GROUP BY key`. Figure 5 illustrates the execution of one sub-epoch batch. Data is pre-packed into buffers and stored in

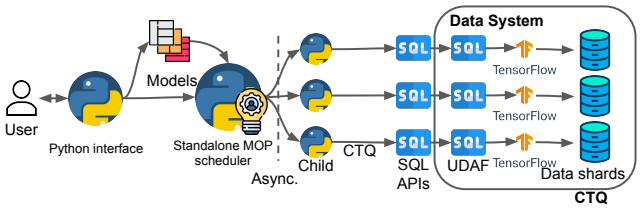

Figure 6: CTQ approach. Partially in-DBMS.

a sharded table. Models are stored similarly in another sharded table. On each physical node of the DBMS, there are multiple rows of data buffers and only one row of model. During the execution, the model row is fed to DL tools to initialize the model, which will be stored as the aggregation state. The worker then scans the data shard and feeds each data buffer to the DL tool, which unpacks the buffers and generates mini-batches for training and updating the stored model. After scanning is done, the scheduler redistributes updated models to different physical nodes by manipulating their distribution keys. The data table, on the other hand, never redistributes.

3.2 Concurrent Targeted Queries (CTQ)

This approach is built upon CTQs, a DBMS feature we will explain shortly. In contrast to UDAF, on the 5 design decisions: it has a Python interface, uses a standalone MOP scheduler and out-of-DBMS model hopping components. It still utilizes DBMS as the execution engine. It also stores and accesses data the way UDAF does. We chose to store and hop models out of the DBMS for implementation simplicity; it is technically possible to keep models governed by DBMS, which can raise this approach's ease of governance (see Section 4.2). Since some core computations run outside the DBMS, we call this approach partially in-DBMS.

We now explain what a CTQ is. In a parallel DBMS, tables are sharded according to distribution keys. When a query only affects one shard, e.g., with a predicate that filters on the distribution key, the query processor will dispatch a query plan to that specific shard only. Such feature is sometimes called targeted query and commonly available [5, 19, 80]. Meanwhile, most DBMSs also allow concurrent queries. Therefore, we can assume more fine-grained control over the execution by issuing targeted queries concurrently. We name this trick Concurrent Targeted Queries (CTQ).

Figure 6 shows the CTQ approach. The user interacts with a Python interface to define models and workloads. It then invokes a standalone MOP scheduler, as described in [85]. This scheduler works differently from the one used in the UDAF approach; it orchestrates DL training by spawning children and using them to issue CTQs. Meanwhile, models are hopped outside the DBMS; we use a shared filesystem for this task. Conceptually, each CTQ is a query of `SELECT udf(model) FROM data WHERE key=x`. Each DBMS node loads the assigned model from the shared filesystem and uses its local data shard to train the model, then checkpoints the updated model back to the filesystem. This concludes one sub-epoch; after every model has visited every data shard once, it is called one epoch.

3.3 Direct Access (DA)

This approach further deviates from UDAF and CTQ by employing a method we call Direct Access, bypassing the entire query processor

Table 2: Conceptual comparison of various architectural approaches of integrating MOP with DBMS. *CTQ can have highest or high ease of governance, depending on whether models are governed by DBMS. †If node RAM is insufficient, swap is needed for DA and the blowup could rise up to 2x.

	Efficiency	Governance	Storage Blowup	Implementation Difficulty	Portability	Design Anti-patterns
UDAF	Medium	Highest	None	Medium	Medium	No
CTQ	High	High-Highest*	None	Medium	Medium	Yes
DA	Highest	High	None - 2x†	Hard	Low	Yes
Cerebro-Spark	Highest	Low	2x	Easy	High	N/A

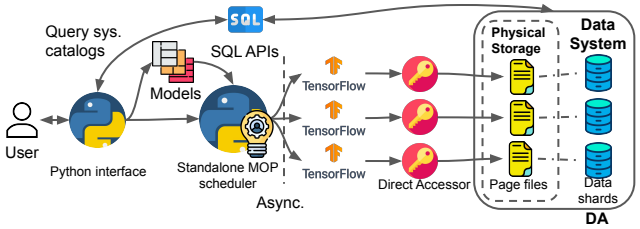

Figure 7: DA approach. In-DB but not in-DBMS.

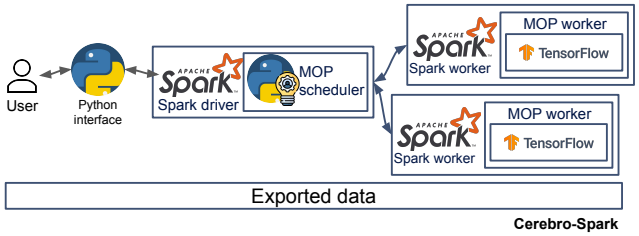

Figure 8: Cerebro-Spark approach. Fully out of DBMS.

of DBMS and accessing the on-disk pagefiles directly. This way, there is enough freedom to plug in and run standalone Cerebro [85] system but without exporting the data. On the 5 design decisions: it has a Python interface and uses the standalone MOP scheduler, workers, and Cerebro's out-of-DBMS model hopping components. It still stores data in the DBMS but reads data directly from the physical pagefiles. This approach is called in-DB but not in-DBMS because although the DBMS still governs data, all executions are out of DBMS.

Figure 7 illustrates DA. The user talks to a Python interface to define workloads and query necessary system catalogs. DA then uses the standalone Cerebro for scheduling and execution. Workers perform training on the data table's sharded pagefiles directly through DAs. DAs first retrieve the pagefiles' location, mapping, layout, and compression information from system catalogs. Then they emulate DBMS's access methods to fetch the pages' contents and feed the data to Cerebro. The latter then consumes the data and runs MOP to train the workload.

3.4 Cerebro-Spark

Cerebro-Spark is a regular out-of-DBMS approach that exports data to filesystem, runs ETL processes, and feeds data to the DL tools. It has a Python interface, standalone MOP scheduler, and model hopping components. It uses the data system (Spark) workers and stores data as plain files. The DBMS does not participate in the training and loses the governance of data.

Figure 8 illustrates the architecture. The user defines workloads through Python APIs. The standalone MOP scheduler initializes MOP workers by embedding them as long-running Spark tasks. It then communicates with these workers and orchestrates the training just like in the standalone Cerebro system.

4 COMPARATIVE ANALYSES OF APPROACHES

With all the approaches introduced, we now compare and analyze them on 6 major axes: runtime efficiency, ease of governance, storage blowup, implementation difficulty, portability, and design anti-patterns. Table 2 shows a conceptual comparison. These axes represent the desiderata and we find that no single approach can fulfill all of them. The more the approach is in-DBMS, the lower the runtime efficiency but the higher the ease of governance and vice versa. We will discuss the reasons in Section 4.1 and 4.2. In terms of storage, Cerebro-Spark has 2x blowup because of exporting; the other approaches have no such blowup. The situation is more complicated on the implementation difficulty and portability axes, and we will give a more rigorous analysis in Section 4.3 and 4.4. As for the last axis, CTQ and DA both introduce design anti-patterns since they are not fully in-DBMS, while UDAF is free of such issues. In the rest of this section, we pick 4 of the most interesting axes and analyze them in more detail.

4.1 Runtime Efficiency

This is one of the most important desiderata. Several factors affect runtime: DL tool invocation, data access, model hopping, and schedule makespans.

DL tool invocation. Both UDAF and CTQ invoke the DL tools through wrappers, whereas DA and Cerebro-Spark do not. Such wrappers may be a source of inefficiency.

Data access. Both UDAF and CTQ access data through DBMS. They could be bottlenecked by data transmission[2], especially when the data is compressed and TOAST-ed [15]. DA can mitigate this issue; by accessing the physical pagefiles directly and caching data in memory, it can provide similar efficiency to Cerebro-Spark, which also reads from filesystem and caches data in memory.

Model hopping. Model hopping might be another source of inefficiency. CTQ, DA, and Cerebro-Spark all do model hopping outside of the DBMS and have similarly low overheads on this end, as [85] pointed out. On the other hand, the UDAF approach relies on the DBMS to hop models through `JOIN` between the data and model tables. This `JOIN` may bring some overheads, especially if the models are large. In later experiments (Section 5.2.3), we will indeed see UDAF is much slower than CTQ on model hopping. However, even

[2]Active development by the MADlib team is going on to mitigate this issue.

Table 3: Notation for discussion on scheduling makespans.

Notation	Description
$\mathbb{M}, M$	Set of models and the cardinality of it
$\mathbb{W}, W$	Set of workers and the cardinality of it
$\mathbb{L}$	Set of each model's per sub-epoch runtime
$\mathbb{L}_i$	For UDAF only. Batch of models scheduled for the i-th sub-epoch
m_x	The x-th model
l_x	The per sub-epoch runtime of the x-th model
l_s	A scale representing the runtimes of fast models
l_m	A scale representing the runtimes of slow models
p	Probability of a model being a fast model
T_u, T_c	End-to-end runtimes for UDAF and CTQ, respectively

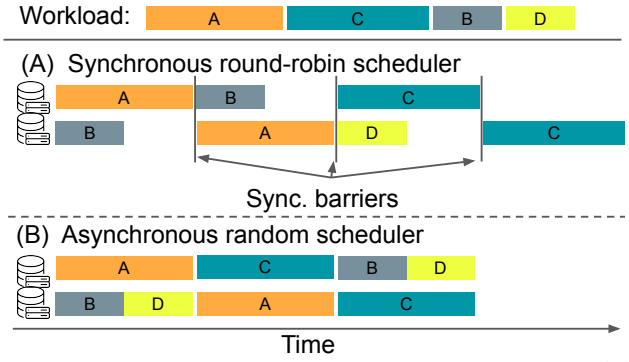

Figure 9: Gantt chart for possible schedules generated by (A) Synchronous round-robin scheduler and (B) Asynchronous random scheduler. The two workers are homogenous but the workload, containing four models, is heterogenous.

for UDAF, model hopping still incurs negligible runtime compared to other components.

Scheduling makespans. CTQ, DA, and Cerebro-Spark all employ the same asynchronous random scheduler. This scheduler's robustness on heterogeneous workloads/workers has been tested in [85]. However, UDAF uses a synchronous round-robin scheduler, which may not work very well with heterogeneity. Figure 9 visualizes one such scenario. How large is the gap between these two schedulers, and could it be a major performance bottleneck? We now analyze the differences theoretically and later verify it empirically in Section 5.2.2. Table 3 presents all notations used in this section.

We compare CTQ against UDAF, as the scheduler is their major difference. Let there be a set of model configs $\mathbb{M}$ and a set of workers $\mathbb{W}$. $|\mathbb{M}| = M$, and $|\mathbb{W}| = W$. Assume the workers to be identical and each worker contains the same amount of data. Let l_x denote the per sub-epoch runtime of model config m_x and $\mathbb{L} = \{l_x\}$. For analysis simplicity, let $\mathbb{L}$ be a two-mode right-tailed distribution, i.e., most models are fast and have per sub-epoch runtime of l_s, while only some are slow and take l_m, $l_m \gg l_s$. Let p be the probability of l_x being fast: $p = Pr(l_x \sim l_s)$. We now analytically compute the per-epoch makespan T_u and T_c for UDAF and CTQ, respectively.

For UDAF, there will be in total M sub-epoch batches, and each batch's runtime will be dominated by the longest running model within this batch, therefore we have in expectation:

$$T_u = \sum_i^M \max(\mathbb{L}_i), \tag{1}$$

where $\mathbb{L}_i = \text{rand}(\mathbb{L}, W)$. $\text{rand}(\mathbb{X}, N)$ means randomly sampling N elements from set $\mathbb{X}$. Assuming that $\max(\mathbb{L}_i) \sim l_s$, meaning every sub-epoch of UDAF run is dominated by l_s, we obtain:

$$T_u = p^W l_s M + (1 - p^W) l_m M. \tag{2}$$

On the other hand with CTQ, assuming M is large enough ($M \gg W$) and the scheduler was capable of load-balancing, we have:

$$T_c = \frac{|\mathbb{L}|}{W} W = W \frac{M\bar{l}}{W} = M\bar{l}. \tag{3}$$

Immediately we have the speedup of CTQ over UDAF:

$$\frac{T_u}{T_c} = \frac{p^W l_s M + (1 - p^W) l_m M}{M\bar{l}} = p^W \frac{l_s}{\bar{l}} + (1 - p^W) \frac{l_m}{\bar{l}}. \tag{4}$$

This indicates the speedup (weak scaling) of CTQ over UDAF is related to the number of workers W and the skewness (represented by $\frac{l_s}{\bar{l}}$ and $\frac{l_m}{\bar{l}}$). Interestingly, note that this speedup is independent of the number of model configs.

Asymptotically, when W goes up, we can see $\frac{T_u}{T_c} \to \frac{l_m}{\bar{l}}$. Define $\eta =: \frac{l_m}{\bar{l}}$. $\eta > 1$ as long as the underlying distribution of $\mathbb{L}$ is right-tailed. This means UDAF will always be faster than CTQ under such circumstance, given sufficient number of workers.

Furthermore, since $\bar{l} = \frac{pl_s M + (1-p) l_m M}{M} = pl_s + (1-p) l_m$, if we expand η, there is:

$$\eta = \frac{l_m}{\bar{l}} = \frac{l_m}{pl_s + (1-p) l_m}. \tag{5}$$

When $p \to 1$ we obtain

$$\eta \to \frac{l_m}{l_s}, \tag{6}$$

which is unbounded and can potentially go to a very high number under extreme circumstances. This indicates when there are only a few outlier models that are time-consuming, the speed-up of CTQ over UDAF is determined by the relative runtime difference of the outlier models and common models. Section 5.2.2 shows an experiment that verifies the above theoretical analysis.

4.2 Ease of Governance

As we mentioned earlier, data governance/provenance now has renewed urgency for all enterprises and even the Web companies, because of the new regulations and laws like GDPR [34] and CCPA [87]. Among the four approaches, UDAF provides the best support for governance/provenance, as it keeps both the dataset and the models in DBMS, which already has built-in governance support. CTQ and DA both use DBMS to govern data. For CTQ, we chose to store models out of DBMS for simplicity, but it is technically possible to keep models in DBMS; this way, it can provide similar ease of governance as UDAF. DA, which relies on external Cerebro, does not manage models with DBMS and thus, loses some ease of governance. Cerebro-Spark does not come with existing governance support and may impose other security issues due to the ad hoc data export and copying. To regain governance, one has to maintain exporting scripts and seek help from external services like MLflow or Kubeflow [62, 81], and such external services are not under the DBMS vendor's control.

Table 4: Workloads.*architectures similar to VGG16 and ResNet50, respectively.

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

4.3 Implementation Difficulty

The out-of-DBMS approach (Cerebro-Spark) is generally the easy one to implement. One naive implementation would be a `SELECT * FROM ...` query followed by some pipelines that feed the exported data to DL tools. The UDAF approach requires more effort to implement the MOP scheduler, wrappers for invoking DL tools, and pipelines that feed data to DL tools and return results to the DBMS. CTQ requires similar efforts as UDAF does, except its scheduler is asynchronous and slightly harder to implement due to concurrency in queries. DA requires the most effort because it needs to implement the whole DBMS table scan method, including locating, unpacking, and reading the pagefiles. If the table is compressed and TOAST-ed [15], then one must also implement the decompression and de-TOAST methods. Simultaneously, because its execution is outside the DBMS, unified memory management is difficult, and it could interfere with other queries. As a result, more careful tuning and setting of configurations are required to implement DA.

4.4 Portability

Portability indicates how much code can be reused if one wants to change the underlying DBMS. The out-of-DBMS approach again excels in this area because it is almost agnostic to the DBMS and can usually be ported easily. UDAF approach is also portable as it requires only UDFs and UDAFs, which are supported in most DBMSs. Medium efforts are needed to export these functions to other DBMSs. CTQ is largely similar to UDAF, except it, in addition, requires the DBMS to support concurrent targeted queries. DA is the less portable option, as it is deeply coupled with the DBMS. Unless the target DBMS employs a similar physical storage layer, to port one existing DA implementation would be difficult.

5 EMPIRICAL COMPARISONS AND ANALYSES

We will first thoroughly compare the end-to-end performance of all the described approaches and study the tradeoff space. Then we will study the effects of factors such as heterogeneous workloads and model sizes. We will also evaluate the scalability of each approach. All of our source code, data, and other artifacts are available at [4]. We compare Cerebro-Spark, UDAF, CTQ, DA, and MADlib MA, which is included as a key baseline. We will test on both GPU-enabled and CPU-only environments. One might wonder how GPUs will be available in practice for users that operate traditional DBMS clusters. As per Greenplum team estimates, at least 80% of its customers continue using on-premise clusters, largely due to privacy and security concerns, especially in the government, financial and health care sectors. Such users are increasingly purchasing GPUs and connecting them to their Greenplum clusters for in-house deployment of DL workloads. In cloud-native DBMSs such as AWS Redshift, one can easily spin up GPU instances and connect them with the DBMS instances. Use of hybrid cloud and public cloud is also increasing. It is not uncommon to run POCs and tests in public cloud with rented GPUs, before purchasing GPUs for in-house production deployment.

Datasets. We use two large benchmark datasets: *ImageNet* [37] and *Criteo* [35]. We use the processing scripts and versions released as part of Cerebro [1, 85]. ImageNet contains 1.2M images with 1000 classes; it has an on-disk size of 250GB. Criteo has 100M data points, binary classes, and an on-disk size of 400GB.

Workloads. We use various DL model selection workloads with different degrees of heterogeneity for different tests. Please refer to each corresponding section for details. We use Adam [58] as the mini-batch SGD method for all tests.

Experimental Setup. We use one cluster on CloudLab [99] with 8 worker nodes and 1 master node. Each node has two Intel Xeon 10-core 2.20 GHz CPUs, 192GB memory, 1TB HDD, and 10 Gbps network. Each worker node also has an Nvidia P100 GPU. For tests with MLP on the Criteo dataset, we disable the GPUs to demonstrate the system's performance under CPU-only setting. All nodes run Ubuntu 16.04. We use TensorFlow v1.12.0, CUDA version 9.0, and cuDNN version 7.4.2. Both datasets are randomly shuffled and split into 8 equal-sized partitions.

5.1 End-to-end Performance Study

We first present the end-to-end results for both ImageNet and Criteo. For ImageNet, we use two different neural architectures and a hyperparameters grid, yielding 16 training configs. For Criteo, we conduct a hyperparameter-tuning-only workload with also 16 training configs. Table 4 offers the details. Such grid search-based model selection is standard in DL practice and still widely used by practitioners [29]. We compare our various architectural approaches with each other. MA is the baseline for this comparison.

For each different approach, separate ETL processes must be done beforehand; we also include the runtimes for these parts. For UDAF, CTQ, and MA, ETL is in-DBMS preprocessing that packs the original data into byte arrays and buffers for the UDAFs to consume. For DA, ETL includes the above processing, accessing tables and TOAST pagefiles, de-TOAST, and loading into the main memory. For Cerebro-Spark, ETL consists of data exporting from DBMS and preprocessing to cast the data formats; we use a distributed Greenplum ETL tool `gpfdist` [112] for exporting and a customized program for preprocessing.

We examine the performance on two fronts: convergence and runtime. Figure 10(A) demonstrates the convergence behaviors for ImageNet. All but MA converge to the same optima, as they are equivalent to sequential SGD. MA, on the other hand, has a convergence problem and learns much slower than the rest. We skip the convergence curves on Criteo for brevity's sake because all methods, including MA, have almost indistinguishable convergence behavior (reaching 99% accuracy quickly).

Table 5: Runtimes and GPU/CPU utilizations of end-to-end tests. We report GPU utilization for ImageNet tests, and CPU utilization for the Criteo ones.

	Approach	End-to-end time	ETL time	Per epoch time excl. ETL	G(C)PU utilization excl. ETL
ImageNet	MA	45.4	2.8	4.26	56.8
	UDAF	51.3	2.8	4.85	49.9
	CTQ	47.9	2.8	4.51	56.2
	DA	28.4	5.4	2.30	70.0
	Cerebro-Spark	27.3	4.4	2.29	70.1
Criteo	MA	47.0	8.6	7.7	44.1
	UDAF	70.7	8.6	12.4	27.1
	CTQ	48.6	8.6	8.0	41.0
	DA	32.2	10.5	4.3	37.4
	Cerebro-Spark	30.8	8.3	4.5	34.8

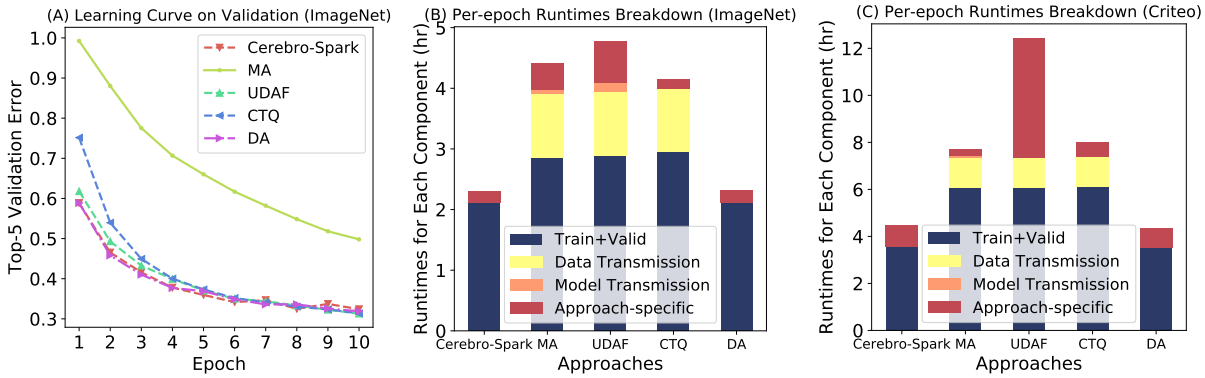

Figure 10: End-to-end tests results. (A): Convergence behavior on ImageNet end-to-end test. (B): Per-epoch breakdown of runtimes for each approach on ImageNet tests. We show the runtimes for three common components, and also the Approach-specific one. (C): Per-epoch breakdown of runtimes for each approach on Criteo tests.

Table 5 summarizes the runtime performance.[3] The three in-DBMS approaches, MA, UDAF, and CTQ, show close speed. MA is the fastest among them, as it has lower communication overhead, but note that it has poor convergence, as Figure 10(A) shows. CTQ is slightly faster than UDAF due to the removal of sub-epoch level synchronization barriers. The benefit is not obvious in this test, but we will drill deeper into the behavior of CTQ in Section 5.2.2. Overall, DA and Cerebro-Spark show the best performance and are indistinguishable in per-epoch runtime. This shows that one can achieve the same high performance as a state-of-the-art out-of-DBMS DL approach while still operating on DB-resident data.

Profiling and breakdowns. To further investigate the root cause of performance differences, we take both datasets and profile every approach by running several more breakdown tests and calculating each execution component's runtime. Excluding the ETL time, Figure 10(B) presents the results for ImageNet, and Figure 10(C) presents results from Criteo tests. We record per-epoch machine time compositions for each worker and take the average among them. Hence, the summations of the runtime numbers are close to but may not be identical to the end-to-end runtimes in Table 5, which are determined by the slowest worker runtime instead of the mean runtime. We break down per-epoch runtimes into four different components:

(1) **Train+Valid**: this is the time spent in the DL tools, including initialization and destruction of models, allocation and freeing of GPU memory, training and validation with GPU, etc. MA, UDAF, and CTQ are less efficient because these in-DBMS approaches invoke the DL tools through wrappers that cause extra overheads.
(2) **Data Transmission**: this is the time spent on transmitting data to the DL tool from its storage. For the in-DBMS approaches, it also includes the data decompression time. Data transmission is non-negligible for the 3 in-DBMS approaches due to data access overheads, while in Cerebro-Spark and DA, the data is ETL-ed and cached in memory; this part costs very little time. But recall from Table 2 that Cerebro-Spark suffers a 2x blowup in storage footprint, while DA does not because it is an in-DB (but not in-DBMS) approach.
(3) **Model Transmission**: this is the time spent on transmitting serialized models between workers. For MA, Model Transmission is the model collecting and broadcasting time; it means model hopping for the rest. All but UDAF and MA are efficient on this end; it is because only these two approaches

[3]Note the runtimes showed in this table may not be directly comparable to those published in [85], as in this paper, we adopted newer implementations for ImageNet model architectures, and we used different on-disk file formats for Criteo.

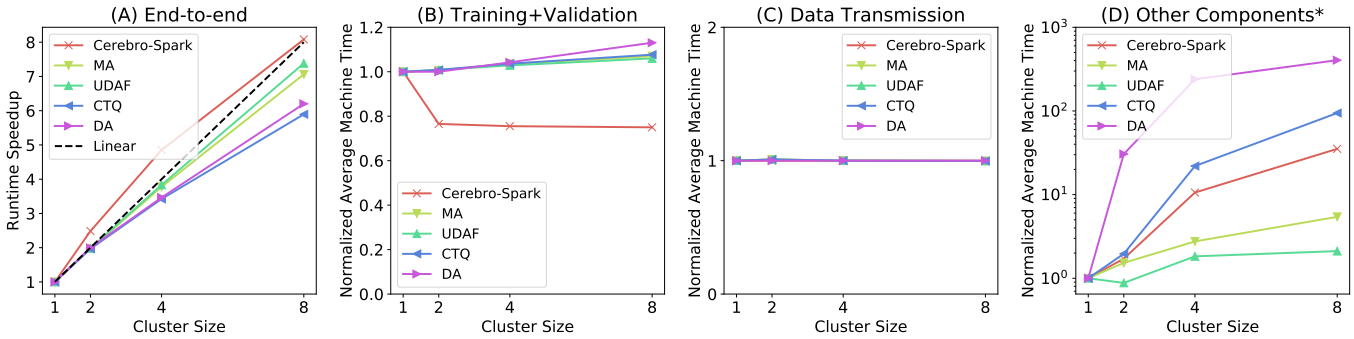

Figure 11: Scalability plots for end-to-end runtimes and also for individual components. (A): End-to-end scalability plot, y-axis shows the speedups with respective to single-node runtime. (B - D): Per-epoch average machine time for each component compared to single-node machine time. The machine time is averaged among all nodes within each cluster. *Other Components: includes Model Transmission and Approach-specific as described in Section 5.1.

are based on database joins for re-distributing models. We will further investigate this performance gap in Section 5.2.3.

(4) **Approach-specific**: for MA, it is the time spent on averaging model weights. For the rest, it means sub-optimal scheduling and/or idling of some workers that finish sooner when no more work is left. Cerebro-Spark, CTQ, and DA use an asynchronous random scheduler and work better for this specific heterogeneous workload. As for UDAF, the performance is affected by its synchronous round-robin scheduler. We further discuss on these two schedulers in Section 5.2.2.

Comparing the Criteo tests to ImageNet tests, we notice two significant differences: (1). Model Transmission time drops for MA and UDAF. The MLP model used in Criteo tests is smaller than the CNNs used for ImageNet. (2). The UDAF approach suffers more from idling in Criteo because it is more heterogeneous than the ImangeNet workload because of the highly disparate batch sizes.

Overall, the in-DBMS approaches suffer from various overheads and are, in general, less efficient than the in-DB but out-of-DBMS DA approach and the fully out-of-DB Cerebro-Spark approach. However, recall that runtime efficiency is not the only criterion for such a system, as we showed earlier in Table 2. There exists a tradeoff space and perhaps no universal optima to the question.

5.2 Drill-down Experiments

5.2.1 *Scalability (strong scaling).*

In this test, we evaluate the strong scalability of various approaches. We used clusters with 1, 2, 4, 8 workers, and load ImageNet to them. We use a workload of 8 homogenous configs (4 learning rates, 2 regularization values, and ResNet50 architecture) trained for one epoch. For Cerebro-Spark, since it internally works the same as the standalone version of Cerebro [85], we re-use the published results from the paper above. All runtimes exclude ETL. Figure 11(A) presents the results.

All of these approaches show close-to-linear scaling. Cerebro-Spark even showed slightly super-linear behavior; this is because when we used only one worker, the whole dataset cannot fit into the main memory and was read from disk. Size 2, 4, 8 clusters could fit the whole dataset in distributed memory, hence the super-linear curve. As for DA, although the ETL-ed data also did not fit in single-node memory, we still enabled caching with disk swapping, which boosted the single node's performance; thus, it did not show super-linearity as Cerebro-Spark did.

To better understand these behaviors, we further drill down each runtime component and evaluate their scalability separately. For this purpose, we collect the average machine time spent on each component from all workers for each different sized cluster; we then report them against the size-1 cluster's machine time. Figures 11(B-D) summarize the results. Flat lines indicate that the component's machine time is constant regardless of cluster size, therefore perfectly scalable. An increasing curve means sub-linearity, and a decreasing one indicates super-linearity.

Figure 11(B) shows the memory issue as explained above and is the source of Cerebro-Spark's super-linearity. Figure 11(C) shows that the Data Transmission component scales linearly for all approaches. The Model Transmission part is minuscule, and thus we report it collectively with the Approach-specific components in Figure 11(D). For DA, CTQ, and Cerebro-Spark, workers may idle relatively more when the number of models approaches the number of workers. The random scheduler they use can yield sub-optimal scheduling under such circumstances. [85] Hence they all show sub-linear scalability, especially when cluster size grows from 4 to 8. On the other hand, UDAF adopts a round-robin scheduler to emulate MOP, which happens to be optimal for this specific homogenous workload; thus, it shows better scalability. MA utilizes all workers and shows no idle time because of scheduling, but the model averaging cost still rises a little when the cluster size grows.

Overall, when the whole dataset fits in a single node's memory, and when the number of models surpasses the number of workers, all these systems should have very similar near-linear scalability.

5.2.2 *CTQ vs UDAF on Heterogeneous Workloads.*

To verify Equation 4 proposed in Section 3.2 and prove the benefit of CTQ over UDAF for heterogeneous workloads, we conduct the following experiments. We truthfully simulate the execution of CTQ and UDAF with heterogeneous workloads and report the completion time for both; then we repeat with different numbers of workers. Because we want to show the extremes and limits thoroughly, we chose to simulate the runs instead of running with real models.

Following the analysis in Section 3.2, let $\mathbb{M}$ be drawn from a Bernoulli distribution: $Pr(l_x = l_s) = p, Pr(l_x = l_m) = 1 - p$. We

Table 6: Workloads used in Section 5.2.3.

	Model	Learning Rate	Lambda Value	Batch Size	Model Size (MB)
Workload 1	MobileNet	{1e-4, 1e-6}	{1e-3, 1e-4, 1e-5, 1e-6}	32	52
Workload 2	ResNet50	"	"	"	294
Workload 3	ResNet152	"	"	"	693

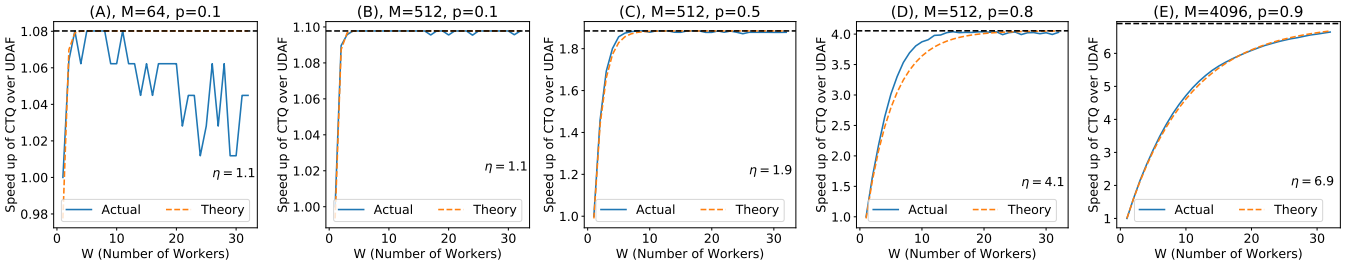

Figure 12: Runtimes of heterogeneous workloads. (A-E) represent different workload configs. Both theoretical bounds and actual runtime gaps are shown. The upper bounds of speedup η are calculated for each workload. NB: Note the different ranges of the Y axes across plots.

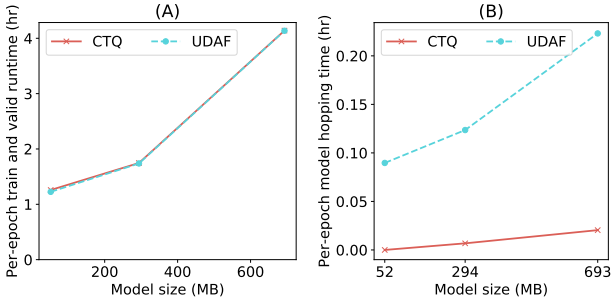

Figure 13: Per-epoch runtime for the three models with different size from Table 6. (A): Time spent on Train+Valid. (B): Time spent on Model Transmission.

assume $l_m/l_s = 20$. We evaluate the speedups of CTQ over UDAF for different numbers of workers W (up to 32). Figure 12 presents the results. Comparing Figure 12(A) with (B), we see that when M is not large enough, the theoretical upper bound is too loose as it assumes a sufficient number of models for the MOP scheduler to load-balance. Comparing Figure 12(B) with (C), we see when p goes up, which means higher heterogeneity and higher right-skewness, CTQ offers drastically higher speedups over UDAF. Furthermore, as Figure 12(E) shows, CTQ's performance gain can continue to increase with even higher skewness η.

Overall, these experiments verify that our theoretical bounds match nicely with the actual runtime gaps. Meanwhile, they also prove our hypothesis that the upper bound of speedup is solely determined by $\eta = \frac{l_s}{l}$, as all lines nicely converge to η eventually. This confirms that CTQ can be a more efficient choice than UDAF when working with highly heterogeneous workloads and/or hardware.

5.2.3 *Effect of model size on UDAF and CTQ.*

The size of the model is typically orders of magnitude smaller than the size of the training dataset. Thus, although model hopping time is proportional to model size, it is usually negligible in large-scale DL. However, this assumption may not hold for the UDAF approach because of the `JOIN` as explained in Section 4.1 Model hopping. We run the following test to investigate model transmission cost with varying model sizes empirically.

We choose 3 hyperparameter tuning workloads on ImageNet. The workloads are shown in Table 6. Each workload features one single model architecture. Model size is reported as the on-disk serialized size. Since these are hyperparameter tuning only, each workload is homogenous. We run each workload for 3 epochs and take the average to get per epoch and per worker machine time breakdown.

Figure 13 presents the results. We profile the runtimes and focus on two runtime parts: Train+Valid and Model Transmission. Figure 13(A) shows no difference in terms of Train+Valid, which is to be expected. Figure 13(B) shows that the CTQ approach imposes little to no bottleneck and is far less sensitive to the model size. However, the UDAF approach suffers more overheads on larger models. This confirms that the JOIN and storing models inside the DB can indeed cause some overheads, although this overhead is not too major (less than 10% in this case).

6 RELATED WORK

ML in Data Systems. There is a long line of work on ML in data systems, both RDBMSs and dataflow systems. The general approach is to implement ML algorithms via UDFs or other APIs exposed by the data system. Apache MADlib [43, 49] is one of the most mature such tools, available on PostgreSQL and Greenplum. The UDAF approach we studied for integrating MOP is already a part of MADlib. Vertica-ML [42], Oracle Machine Learning [13], Microsoft SQL Server ML Services [11], and Google BigQuery [6] are other prominent examples of in-RDBMS ML tools. [93] brings ML to column stores. MLlib [79] and MLlib* [128] use Spark's APIs to implement various ML algorithms. Mahout [20] is a distributed ML system on top of dataflow systems. Increasingly, more data system builders want to integrate with DL via wrappers that invoke popular DL tools: Horovod on Spark [8], TensorFrames [14], and PS2 [127] are examples. More generally, the DBMS and cloud industry believe DBMSs will continue to play a key role in enterprise ML [16].

Some works also expand DBMS support for ML. Raven [55] deeply integrates ML runtimes into a DBMS. UDA-GIST [69] expands support for algorithms that are both data-parallel and state-parallel. [78] adds linear algebra support to RDBMS. [123] proposes a "tensor-relational" algebra towards declarative ML. TensorDB [57] is a system for in-DBMS tensor decomposition. [56] focuses on in-DBMS sparse tensors for ML. DB4ML [53] expedites iterative ML algorithms via asynchrony. [44] discusses declarative model weights distribution/aggregation for data-parallel ML. [52] adds better support for recursion to RDBMS for distributed ML. MLearn [103] is a declarative language for in-DBMS ML. AIDA [39] provides an abstraction for in-DBMS data analytics; it uses DBMS for relational operations and embeds Python for linear algebra.

All of the above works are complementary to ours. To the best of our knowledge, our paper is the first to study system design alternatives and tradeoffs for enabling DL workloads on DBMSs. Specifically, we focus on bringing a recently published hybrid parallel execution approach for DL model selection, MOP, to the traditionally bulk-synchronous parallel world of DBMSs.

Custom ML Systems. There is also a long line of work on custom systems for ML training/model selection. FlexPS [50] and Lapse [98] are both optimizations to Parameter Server [71]. Horovod [104] brings in decentralized communication to boost runtime efficiency. Vizier [45] and Rafiki [117] are systems for task-parallel model selection; Ray [74, 82] was initially designed for reinforcement learning but recently also supports task-parallel model selection. Singa [88, 116] and SystemML [26–28] are end-to-end platforms for ML that supports various distributed training. Visus [101] and Ease.ml [96, 97] are examples of AutoML systems that manage the whole ML lifecycle, including both data management and model selection. Croosbow [59] and Ako [119] are systems for better resource scheduling and utilization for ML. [38] handles collaborative working environments for ML development. Litz [92] focuses on the elasticity of distributed ML.

All these works are also complementary to ours because they study standalone ML/DL execution, not integration with data systems. While some of them may be faster than in-DBMS ML tools, as we explained in depth in this paper, ML practitioners, especially in enterprises, grapple with a more complex Pareto frontier beyond just runtimes. Our paper lays out these tradeoffs in bringing DL workloads closer to DB-resident data. That said, the CTQ approach we studied was in part inspired by the pervasive use of task parallelism in such custom ML systems, including in Cerebro as we explained earlier. More generally, we believe these historically distinct work lines–custom ML systems and ML on data systems–can learn a lot from each other.

Data Management for ML. More generally, data management for ML is a hot and pressing research topic [25, 64, 91, 102]. Such works aim to optimize or automate data management tasks in ML workflows to reduce user burden. Data Programming [95] and Snorkel [94] focus on ML training data creation through weak supervision and generative models. DeepDive [124] is a system for knowledge base construction. ModelDB [110, 111], TFX [22], Mlog [72], and MLFlow [81] all add data management and model management support for ML. ARDA [33] uses DBMS for data augmentation and feature selection tasks. Activeclean [61], boostclean [60] and [76] focus on data cleaning and debugging for ML. Vamsa [86] supports data lineage tracking for Python ML scripts. [48] proposes the concept of model materialization and reuse to speed up ML training.

All these works are also largely orthogonal to ours, since our focus is specifically on tradeoffs of in-DBMS execution of DL model selection, not auxiliary data/model management capabilities. Lessons from our work can be easily integrated with these other tools to enhance end-to-end support for ML applications for DB users.

Data Access and Pipeline Optimizations for ML. There is much prior work on optimizing ML+data processing pipelines. Lara [67], Alpine-Meadow [106], and KeystoneML [107] all allow the user to define pipelines with their APIs and perform pipeline-level optimizations. Helix [121] injects intelligent caching and reuse between training iterations to reduce redundant work. [40] proposes linear algebra that could work upon compressed data, thus saving decompression time. [68] introduces a tuple-oriented compression scheme for matrix and mini-batch SGD computations directly on compressed data.

The above works are largely orthogonal to our paper, since our goal is *not* to devise novel optimization schemes or systems but rather to analytically and empirically study the tradeoffs of alternative approaches to bring DL workloads to DB-resident data. That said, the DA approach we studied was in part inspired by such prior work on ML operating more directly on the raw stored data. It is interesting future work to integrate more such optimizations into systems that bring DL closer to DB-resident data.

7 CONCLUSION

We study the question of how to bring DL model selection workloads closer to DB-resident data, a capability of growing interest to DBMS and cloud vendors. We explain a set of practical desiderata based on lessons from past in-DBMS ML work, including runtime efficiency, ease of governance, and implementation difficulty. We discuss a spectrum of four canonical approaches and perform comparative conceptual and formal analyses of their tradeoffs, as well as empirical comparisons using implementations on Greenplum. We find that there is no simple answer on a "best" approach and an interesting Pareto frontier exists. Our work could spur interesting discussions among DBMS and cloud vendors, as well as DB researchers working on improving DL support for DB users.

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