RecD: Deduplication for End-to-End Deep Learning Recommendation Model Training Infrastructure

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**ABSTRACT**

We present RecD (Recommendation Deduplication), a suite of end-to-end infrastructure optimizations across the Deep Learning Recommendation Model (DLRM) training pipeline. RecD addresses immense storage, preprocessing, and training overheads caused by feature duplication inherent in industry-scale DLRM training datasets. Feature duplication arises because DLRM datasets are generated from interactions. While each user session can generate multiple training samples, many features' values do not change across these samples. We demonstrate how RecD exploits this property, end-to-end, across a deployed training pipeline. RecD optimizes data generation pipelines to decrease dataset storage and preprocessing resource demands and to maximize duplication within a training batch. RecD introduces a new tensor format, InverseKeyedJaggedTensors (IKJTs), to deduplicate feature values in each batch. We show how DLRM model architectures can leverage IKJTs to drastically increase training throughput. RecD improves the training and preprocessing throughput and storage efficiency by up to 2.48×, 1.79×, and 3.71×, respectively, in an industry-scale DLRM training system.

1 **INTRODUCTION**

Machine learning (ML) infrastructure is one of the most dominant components of industry-scale datacenters. For example, ML consumes over 70% of FLOPs at Google (Patterson et al., 2022). To support the computational demands of ML, and especially training, companies such as Google (Lardinois, 2022), Meta (Mudigere et al., 2022; Meta, 2022), and AWS (AWS, 2022) are deploying massive clusters consisting of tens of thousands of accelerators.

Deep learning recommendation model (DLRM) training is a principal industrial use-case for these clusters. For example, DLRM training dominates ML capacity across Meta’s fleet (Naumov et al., 2020). This demand is driven by the ubiquity of DLRMs across industry, as they underlie critical services from Google (Anil et al., 2022; Li et al., 2020; Zhao et al., 2019), Taobao (Ge et al., 2018), Meta (Meta, 2019; Hazelwood et al., 2018; Acun et al., 2021), and others. DLRM training clusters are fed by a data storage and ingestion (DSI) pipeline — systems that generate, store, and preprocess training data — which can demand more power consumption than what is required by the training accelerators (trainers) themselves (Zhao et al., 2022). To train larger, more complex, and more accurate models, it is critical to improve the performance and efficiency of the end-to-end DLRM training pipeline, from DSI to trainers.

To this end, this paper presents a suite of optimizations, called RecD, spanning the DLRM training pipeline. RecD exploits the inherent session-centric nature of DLRM datasets. DLRM training samples are generated from user interactions which query industrial recommendation models. Each user’s session typically requires numerous inferences, and thus produces many training samples (Wang et al., 2021). However, the features that largely compose each sample likely remain static throughout each session. For example, an e-commerce DLRM dataset may contain a user feature representing the sequence of the last \(N\) items added to a shopper’s cart. The e-commerce site may serve recommendations throughout a user’s shopping session, but if the shopper does not add a new item, each of the session’s samples will contain the same values for that feature.

While prior work has mentioned feature duplication (Ge et al., 2018; Gai et al., 2017), none has characterized its prevalence in industry-scale datasets nor provided solutions that optimize for it across the training pipeline. Current pipelines spend considerable resources storing, preprocessing, and training over duplicate features. These overheads constrain industry-scale training infrastructures from supporting larger datasets, longer features, and more complex modeling techniques (e.g., attention) that yield more accurate models (Ardalani et al., 2022; de Souza Pereira Moreira...
We begin the paper with an in-depth characterization of how session-centricity generates significant feature value duplication in datasets used by an industrial DLRM training pipeline. Each session produces many samples (16.5 on average), and feature values are largely duplicated across the session’s samples (81.6 – 89.4% on average). RecD addresses the significant storage, preprocessing, and training overheads caused by duplication throughout the DLRM training pipeline.

RecD begins at data generation by sharding raw inference logs by session ID to improve compression ratios in Scribe (Karpathiotakis et al., 2019), a distributed message passing system. These logs are ingested by ETL engines to produce training samples. RecD coalesces each session’s samples within a training batch. Not only does this reduce dataset sizes due to native compression, it also allows RecD to convert each batch to a new tensor format during data reading, InverseKeyedJaggedTensors (IKJTs), that deduplicates feature values.

IKJTs require minimal resource overheads to generate and use for preprocessing and training. Meanwhile, they allow readers, which preprocess data, and trainers to operate on deduplicated tensors, significantly reducing resource demands across the training pipeline. We explore these benefits. We present how DLRM architectures can leverage IKJTs to reduce GPU compute, network, and memory resource requirements — improving training throughput and enabling more powerful modeling techniques. In summary:

- We provide a characterization using petabyte-scale industrial DLRM datasets showing how feature duplication is inherent in DLRM training pipelines. We discuss the opportunities and challenges of deduplication.
- We present necessary optimizations made in the data storage and ingestion pipeline to enable a novel tensor format, IKJTs, that deduplicates features in each training batch.
- We show how IKJTs improve DLRM training throughput and resource utilization by eliminating redundant compute, memory, and network usage during training.
- We evaluate on industrial DLRMs. RecD improves training and preprocessing throughput and storage efficiency by up to 2.48×, 1.79×, and 3.71×, respectively.

## 2 Background

Figure 1 shows an end-to-end industrial training pipeline (Zhao et al., 2022), with DSI and training services.

### 2.1 Data Storage and Ingestion

**Data Generation.** Training data is continuously generated from deployed recommendation services. User-facing services request batches of inferences throughout a user’s session. For each batch of requests, features corresponding to the user and potentially recommended items are retrieved from a feature store and are used as input to the DLRM to generate relevant predictions. Since features continuously change, inference servers log features for each request to avoid data leakage (Kaufman et al., 2012). Given predictions, user-facing services generate relevant impressions of items and log events (i.e., impression outcomes). Logs are aggregated in Scribe, a global distributed messaging system (Karpathiotakis et al., 2019).

Streaming and batch processing engines, such as Spark (Zaharia et al., 2012), ingest data from Scribe. These engines join raw features and events to produce labeled samples. Training samples are subsequently landed into time partitioned (e.g., hourly) Hive tables (Thusoo et al., 2009). To maintain data freshness, new table partitions are constantly landed and old partitions are deleted.

**Dataset Schema and Storage.** Each training sample, corresponding to an impression and outcome, is stored as a structured row containing features and labels. Features represent almost all of the bytes within a sample. DLRMs require two types of features: dense and sparse. Dense features represent continuous values, such as time, and are stored as a map from feature key to a float value. Sparse features represent categorical values, such as item IDs, and are stored in map columns that map a feature key to its value, typically a variable-length list of item IDs. Compared to dense features, sparse features require significantly more storage, preprocessing, and training resources across the DLRM training pipeline (Zhao et al., 2022; Naumov et al., 2020; Sethi et al., 2022).

Hive partitions are stored as columnar DWRF (Zhao et al., 2022).
Figure 2 shows how DLRMs are synchronously trained using hybrid parallelism across multiple GPUs. Dashed lines show collective communication across model-parallel and data-parallel modules.

2.2 DLRM Training at Scale

Figure 2 shows how a typical DLRM (Naumov et al., 2019) is synchronously trained across multiple GPUs. DLRMs primarily consist of multilayer perceptrons (MLPs) and embedding tables (EMBs) composed into three main architectural components. EMBs ingest sparse feature lists and produce a dense activation vector for each list element. A pooling function (e.g., average, sum, or max) aggregates activations for each sparse feature. Meanwhile, a bottom MLP transforms dense features into a dense representation with the same dimensionality as embedding vectors. An interaction layer explicitly computes second-order interactions across dense and sparse features (e.g., via pairwise dot product). A top MLP and sigmoid processes the result to produce a probability output (e.g., click-through rate).

DLRMs are trained using hybrid parallelism across multiple GPUs. MLPs are copied across GPUs in a distributed data parallel (DDP) fashion, while EMBs are sharded across GPUs via distributed model parallelism (DMP) due to their large size. During each training iteration, each GPU ingests a local batch from the reader tier. A sparse data distribution (SDD) step first aggregates the appropriate feature values, across all local batches, to the corresponding GPU using an all-to-all collective (NVIDIA, 2022) across all GPUs. After the EMB lookup and pooling, another all-to-all distributes embedding vectors back to their original GPUs, as feature interaction and the top MLP is data parallel. After calculating the loss, an all-reduce aggregates gradients to update MLPs. Similarly, an all-to-all synchronizes EMB parameter updates during the backward pass. Thus, the iteration time is determined by both the per-GPU compute and memory bandwidth resources (for MLPs, interactions, pooling, and EMB lookups), as well as the backend network bandwidth and latency (for collective communications).

Scaling Systems for DLRMs. Improving DLRM accuracy necessitates systems efficiency and throughput optimizations across the training pipeline. For example, (Ardalani et al., 2022) showed that data scaling significantly improves DLRM performance. Supporting growing dataset volumes requires not only more efficient storage, but also improved reader and trainer throughputs to complete training within a reasonable amount of time. Meanwhile, recent DLRM architectures focus on capturing users’ long-term interests via a sequential history of interactions (Pi et al., 2019; Li et al., 2019; Chen et al., 2019). These architectures use long sequence features and attention mechanisms, such as transformers (Vaswani et al., 2017), to pool embeddings across many sequence features. They demand significant GPU compute, memory, and network resources. Thus, optimizing for DSI and training performance and efficiency is increasingly urgent as resource demands continue to grow.

3 Understanding Data Reuse

To understand the opportunity for RecD, we explore the prevalence of duplication within industry-scale datasets. We focus on sparse features because they a) are prone to duplication as we characterize next, and b) demand significantly more training pipeline resources than dense features (Section 2) and thus present a more attractive optimization target.

Duplication arises because sparse user features rarely change across impressions within a session. For example, consider social media features $f_{like}$ and $f_{share}$, which contain a user’s last N posts they liked and shared, respectively. During a session, a user may view multiple posts (impressions). While each impression may generate a training sample, $f_{like}$ and $f_{share}$ will be exactly the same across

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1A session is a set of user impressions in a fixed time window.
We observe that, on average, each session generates 16 samples per session. We first quantify how often each feature’s value changes across samples. On average, across all features, 0% of feature values are an exact duplicate. This validates our assumption that many DLRM features are not updated across a session’s samples.

Specifically, DLRM sparse features largely reflect either user or item traits. User sparse features (e.g., last N liked item IDs) are largely duplicated across a user’s samples. Item features (e.g., the item ID that is evaluated for recommendation) are less duplicated since many different items are ranked in a given session. Figure 4 shows this distinction – user features comprise the vast majority of dataset volume and accordingly represent the large subset of features with high duplication. Meanwhile, item features exhibit less duplication, representing the subset of features right of the knee. We expect increased reliance on user features, and thus higher feature duplication, since recommender systems are increasingly focusing on larger user interaction history features compared to item metadata (Section 2.2).

For highly-duplicated user features, even if its values change across samples, we expect the majority of its list IDs to remain the same. We thus repeated the analysis on an individual list ID basis. For example, suppose feature $x$ contained 100 IDs across 2 training samples. $x$ may be updated by appending a new ID and shifting its list by one, resulting in $99/200 = 49.5\%$ partial duplication. Figure 4 shows how on average across all features, 83.9% of feature values within each feature list are duplicated. Many non-exact duplicate samples within the session contain partial duplicates. Finally, it is important to note that not all feature lists have the same length. To understand how many bytes are duplicated, we weigh each feature in our prior analysis by its respective average length. We find that 81.6% and 89.4% of all IDs in feature values (i.e., bytes) are exact and partial duplicates, respectively, suggesting that longer features have slightly more exact and partial duplicates.

**Summary.** The vast majority of feature values are duplicated within the industry-scale DLRM dataset. While significant deduplication opportunities exist, they require each session’s samples to be co-located within training batches. Thus, trainer-only solutions are insufficient — optimizations must be co-designed across the end-to-end training pipeline.

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**Figure 3.** Histogram of the number of samples per session within an hourly partition (left) and 4096 batch (right) from the partition.

**Figure 4.** Percent of exact (left) and partial (right) duplicate values across sparse features within an hourly partition.
### 4 RecD in data storage and ingestion

RecD implements these optimizations, summarized in Table 1, throughout the industrial pipeline shown in Figure 1.

#### 4.1 Data Generation and Storage

**Log Sharding.** Scribe is a message passing service which logically aggregates and buffers raw logs from each inference server. To load balance, Scribe consistently hashes the message and routes each to a shard on a physical storage node, which buffers and compresses messages in memory and on disk. Unfortunately, the default hashing configuration distributes logs for each session randomly across shards. RecD configures Scribe to instead use session IDs as the shard key, improving the “compressibility” of data within each shard. Thus, we can both reduce the number of Scribe storage nodes and the amount of network bandwidth needed for downstream ETL jobs to ingest logs.

**Clustering by Session.** While improved sharding increases the locality of a session’s logs, it does not guarantee that a session’s training samples are adjacent within the dataset. This grouping is needed for downstream systems to deduplicate features. Thus, RecD adds a data generation ETL job, which clusters partitions by session ID and sorts by log timestamp. As with Scribe, we also expect two direct benefits from ETL clustering. First, each file’s stripes are compressed using black-box compression, e.g. zstd (Zstandard, 2022). Ensuring that each stripe contains multiple rows for a given session increases compression ratios and thus reduces dataset storage requirements. Secondly, smaller files also reduce compute and network resources needed to read samples during online preprocessing.

#### 4.2 Tensor Encoding for Deduplication

Figure 5 shows how reader nodes generate preprocessed tensors for each training job. Each reader reads batches of samples, converts rows to tensors, and preprocesses tensors.

A **Feature Conversion** step copies data from raw batches of rows, read into memory as byte arrays, into structured tensors. The typical tensor format used for sparse features is a KeyedJaggedTensor (KJT) (PyTorch, 2022). A KJT maps a key (i.e., the feature key) to a JaggedTensor — a tensor with a jagged dimension (i.e., different length slices). For example, Figure 5 shows how a batch of 3 rows for feature *a* is transformed into a KJT with two slices representing the feature’s values and offsets for the batch. The offsets slice has an entry for each row, with offsets[i] pointing to the starting index in the values slice for row *i*. The length of the feature for row *i* is calculated from offsets[i] to offsets[i+1] — but not offsets[i] (or |values| — offsets[i] for the last row). In the example, feature *a* has 2× duplication in the values slice as rows 0 and 2 both contain [1, 2].

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**Table 1. Overview of RecD optimizations made throughout the industry-scale training pipeline.**

| Optimization | Target System | Benefit |
|--------------|----------------|---------|
| O1: Log Sharding (§4.1) | Scribe | Improves black-box compression ratios to reduce Scribe network RX/TX and storage demands. |
| O2: Cluster by Session (§4.1) | ETL | Session sample co-location enables readers/trainers to exploit duplicate features. Improves file compression ratios, reducing storage and read IOPS demands. |
| O3: Inverse KJT Preproc. (§4.2) | Readers | New tensor encoding allows downstream preprocessing/training operations to use deduplicated features, enabling significant resource savings. |
| O4: Deduplicated EMB (§4.3) | Readers | IKJT preprocessing modules reduce preprocessing compute demands. Deduplicated outputs require less NW bandwidth between readers and trainers. |
| O5: Deduplicated Compute (§5) | Trainers | Reduced memory copy overheads by enabling index select without first converting jagged features, lookups, and activations. |
| O6: JaggedIndex-Select (§5) | Trainers | Reduced memory copy overheads by enabling index select without first converting jagged tensors to a dense representation. |
| O7: Deduplicated Compute (§5) | Trainers | Reduced compute for sparse feature modules (especially attention pooling) by allowing them to operate on deduplicated tensors. |
**InverseKeyedJaggedTensor.** To deduplicate feature values, **RecD** introduces a new inverse KJT format. Figure 5 shows how ML engineers can specify a `dedup_sparse_features` field in the PyTorch DataLoader, which is a `List[List[featureKey]]`, containing lists of feature groups to deduplicate. **RecD** deduplicates each feature group to an InverseKeyedJaggedTensor (IKJT) during feature conversion. Of course, users can still generate KJT for features not exhibiting high duplication.

**RecD** deduplicates features by detecting and avoiding duplicate copies during feature conversion. An IKJT instead adds an additional inverse lookup slice, where `inverse_lookup[i]` points to the respective entry in the deduplicated offsets slice for row `i` in the batch. offsets encodes the values slice as before. In our example, feature `b` contains duplicate values for rows 0 and 2. Thus `inverse_lookup[0] == inverse_lookup[2]`, with both pointing to `offset[0]` which encodes the duplicate values `[3, 4, 5]`. IKJTs avoid storing a second copy of `[3, 4, 5]` in the values slice. Since exact matches are the vast majority of duplication (Section 3), we focus on deduplicating exact matches and discuss supporting partial matches in Section 7.

**Grouped IKJTs.** Users can deduplicate multiple features within a single IKJT. Grouped IKJTs are designed for features updated synchronously across samples and thus share inverse lookup values. For example, an e-commerce model may use two features which track the item ID and seller ID for items added to a user’s cart. Since both features track the same item sequence, they are both updated at the same time (i.e., when a new item is added). As we explore in Section 5, grouped IKJTs are designed to enable additional optimizations during each training iteration.

In Figure 5, features `c` and `d` are deduplicated as a group. For both features, rows 0 and 1 are duplicates. Thus, **RecD** uses a common inverse lookup to reference the offsets slice for both features, even if their respective offsets or values slices are different. For example, `inverse_lookup[0]` will map to `[7, 8]` for feature `c` and `[9]` for feature `d`. In the event that grouped feature values are not synchronously updated across samples, we will not deduplicate the corresponding unsynchronized rows to ensure that the inverse lookup invariant is maintained.

Using IKJTs. Not all features may be worth deduplicating. To understand the value of deduplication, we use the following analytical model for a feature `f`. `S` is the average number of samples per session. `B` is the batch size. `d(f)` is the probability that the `f`’s value will remain the same across adjacent rows. `l(f)` is the average length of `f`.

\[
DedupeLen(f) = l(f) \times B \times (1 - (S - 1) \times S^{-1} \times d(f))
\]

\[
DedupeFactor(f) = l(f) \times B / DedupeLen(f)
\]

Specifically, `DedupeLen(f)` expresses the size of the values slice after deduplicating `f` for each training batch. The deduplication factor, `DedupeFactor(f)`, is calculated as the ratio of the original values slice length to `DedupeLen(f)`. For example, suppose `B = S = 3`, `l(b) = 3`, and `d(b) = 0.5` for feature `b` in Figure 5. Deduplicating `b` results in `DedupeLen(b) = 6` and `DedupeFactor(b) = 1.5`. The total amount of feature values deduplicated increases with higher `S`, `l(f)`, and `d(f)`, which aligns (i.e., increases) with data scaling trends (Section 2.2).

While `inverse_lookup` and offsets requires more elements than offsets alone (up to `B`), the overhead is negligible as for most features `l(f) \times B >> B`. Furthermore, as we discuss in Section 5, because only values and offsets tensors are communicated across GPUs, IKJTs strictly decrease over-the-network tensor sizes during training. Finally, `DedupeFactor(f)` provides an initial guidance on the impact of deduplicating `f`. We typically deduplicate features with `DedupeFactor(f) > 1.5`. However, the actual performance benefit depends on how well readers and trainers can use IKJTs, as we explore next and discuss in Section 7.

### 4.3 Preprocessing over IKJTs.

After feature conversion, each reader node preprocesses tensors using a set of user-provided TorchScript modules. If a user deduplicates a feature, we automatically add a wrapper that transparently supports preprocessing over IKJTs. Since the original function used KJT, the wrapper simply provides the offsets and values slices from the IKJT held in memory, saving significant compute resources by avoiding preprocessing duplicate values. Deduplicated preprocessing functions also output IKJTs. This reduces network bandwidth requirements between reader and trainer nodes and allows trainers to further leverage IKJTs.

## 5 RecD in Training

Building on our newly proposed IKJT tensor format, we design a series of **RecD** PyTorch modules as direct replacements for DLRM embedding and pooling operations. The
IKJT format generated by readers enables a host of optimizations at the trainer, summarized in Table 1. As shown in Figure 6, these modules operate on deduplicated (i.e., IKJT) tensors during the forward pass, reducing resources spent operating over duplicate sparse feature values.

**Sparse Data Distribution.** After receiving a batch of samples, each GPU executes a sparse data distribution (SDD) step. Using an all-to-all collective, SDD coalesces a global batch only containing the respective features corresponding to each GPU’s model-parallel EMBs. Previously, KJTs required sending significant amounts of duplicate feature values over the network. With RecD, deduplicated IKJT value and offset slices are sent instead (inverse Lookup slices are kept local). RecD thus reduces the amount of bytes distributed during SDD by DedupeFactor(f) for each feature f. Since SDD runs before any embedding lookups, reducing the amount of data over the network in each iteration directly improves training throughput.

**EMB Lookups.** After SDD, each trainer needs to translate every feature value in the KJT into an embedding by performing a lookup in each EMB. By using IKJTs, the length of the values slice is reduced by DedupeFactor(f), reducing the overall number of EMB lookups we need to perform in each iteration and thus required memory bandwidth.

**EMB Inputs and Activations.** Each GPU also needs to allocate significant dynamic memory to store the feature inputs and EMB activations of each sparse value. This is especially true of long length sequence models. For example, a single feature f with \(l(f) = 1000\), \(B = 4096\), and an EMB dimension of 128 would require \(4096 \times 1000 \times 128 \times 4B \approx 2GB\) of GPU memory to store activations. By performing lookups using IKJT values, we directly reduce the amount of dynamic GPU memory required by DedupeFactor(f).

**Deduplicated Pooling.** DLRMs use a set of pooling modules (e.g., sum, avg.) that operate on the EMB activations prior to feature interaction. Recent trends have motivated more complex pooling modules, such as transformers and other attention mechanisms (Pi et al., 2019; Li et al., 2019), which operate over multiple long-length sequence features. These modules require significant GPU resources.

To reduce the computational and memory overhead for these sequential pooling modules, RecD allows users to run compute modules with IKJTs as inputs. Specifically, by ensuring that the inverse Lookup slice is shared across all features within an IKJT, we can deduplicate compute by simply operating on the deduplicated values and offsets. For example, assume a module element-wise sums values for each row across features c and d in the example in Figure 5. Using KJTs, the GPU computes \([7 + 8 + 9, 7 + 8 + 9, 10 + 11] = [24, 24, 21]\). With IKJTs, we instead compute \([7 + 8 + 9, 10 + 11] = [24, 21]\) and simply use the shared inverse Lookup to expand the output to \([24, 24, 21]\). By applying this technique to expensive attention pooling modules, we reduce the compute demand by DedupeFactor(f) for each sequence feature f.

**Deduplicated EMB.** Since the output of pooling layers are still in the IKJT format, we can get more network savings during the all-to-all that broadcasts pooled embeddings back to each GPU for feature interaction.

**Jagged Index Select.** Before feature interaction, IKJTs must be converted back to a KJT to be interacted with other non-deduplicated features. We use torch.index select to perform this conversion. Prior to RecD, index select could only operate on dense, not jagged tensors. We needed to first convert jagged tensors into dense tensors (e.g., via padding), incurring large memory overheads. We implemented a jagged index select to operate over jagged tensors, eliminating this overhead.

**Summary.** As summarized in Figure 6, IKJTs enable a host of GPU network, memory, memory bandwidth, and compute optimizations during training. These optimizations improve training throughput and reduce GPU resource demands, allowing us to train more complex models at a faster rate.

## 6 Evaluation

### 6.1 End-to-end Performance Optimizations

RecD improves the performance and efficiency of the entire training pipeline, including storage, readers, and trainers. To study each component, we used three representative industrial DLRMs, RM1, RM2, and RM3, designed around the core DLRM architecture (Naumov et al., 2019). RM1, RM2, and RM3 contain \(O(10^6)\), \(O(10^9)\), and \(O(10^9)\) parameters with \(O(10GB)\), \(O(100GB)\), and \(O(100GB)\) of embedding tables, respectively. Embedding dimensions range from 64-1024 across each RM.

We evaluate on a trainer tier consisting of ZionEX training nodes (Mudigere et al., 2022). Each ZionEX node contains 8 NVIDIA A100 GPUs with a total of 320 GB HBM and 12.4 TB/s of memory bandwidth. Intra-node communication across GPUs occurs via NVLink. Each GPU is equipped with a 200 Gbps RoCE NIC for inter-node communication over a dedicated RoCE backend network. Input data is supplied by 4 host CPU sockets, each with a 100 Gbps NIC that ingests data from a tier of DPP (Zhao et al., 2022) readers. Each reader is a general-purpose, x86 CPU server with 18 cores, a 12.5 Gbps NIC, and 64 GB of memory. Readers read data from each RM’s respective \(O(100PB)\) industrial dataset stored within the Tectonic file system (Pan et al., 2021).

For each RM, we used the default baseline configuration, with \(RM_1\), \(RM_2\), and \(RM_3\) using a batch size of 2048,
2048, and 1152, and 48, 48, and 64 GPUs, respectively. We then enabled the full suite of RecD optimizations for each RM, which allowed us to increase the batch size for RM1 and RM3 to 6144 and 2048, respectively. For RM2, we could not substantially increase batch size beyond 2048. For RM1, we deduplicated 16 sequence features in 5 groups. RM2 and RM3 deduplicated 6 and 11 sequence features, respectively, in one group. Each RM also deduplicated an additional \(\approx 100\) features that were element-wise (e.g., sum, max) pooled. DedupeFactor was \(\approx 4 - 15\) for deduplicated features. We used a clustered table for RecD models containing the same data as the baseline table. We kept all other hyper parameters the same and scaled the number of readers to provide sufficient throughput to avoid data stalls in all configurations.

Figure 7 shows how trainer throughput, reader throughput, and storage compression ratio improved with respect to the baseline for each RM. Trainer throughput is the total samples per second processed by all trainers. Since we scale the number of readers based on trainer throughput, we report the samples per second processed on average by each reader. Finally, we report the compression ratio of the clustered table’s Tectonic files relative to the baseline table. RecD improved trainer throughput by 2.48 \(\times\), 1.25 \(\times\), and 1.43 \(\times\), significantly decreasing training job latencies. Similarly, each reader processed samples 1.79 \(\times\), 1.38 \(\times\), and 1.36 \(\times\) faster, reducing the number of readers needed for each training job by the same amount. We explore in Section 6.2 and 6.3 why RM1’s increased use of sequence features allowed RecD to further increase trainer and reader throughput, respectively, compared to RM2 and RM3. Clustered tables improved the compression ratio by 3.71 \(\times\) (RM1 and RM2 used the same table) and 2.06 \(\times\), directly improving storage efficiency by reducing the number of storage nodes needed to store and serve each RM’s dataset. RM1 and RM3’s table exhibited higher samples per session than RM2’s table, leading to a larger increase in compression after co-locating each session’s samples within a file stripe. Finally, we increased the compression ratio at Scribe from 1.50 \(\times\) to 2.25 \(\times\) by sharding logs by session ID.

### 6.2 Why does RecD improve trainer throughput?

**Iteration Breakdown.** To understand where RecD improves training throughput, we ran a training job for each RM using the same batch size as the baseline. Figure 8 shows a breakdown of the iteration latency of the RecD training job normalized to the baseline iteration latency, averaged across all GPUs. Specifically, we show exposed latency (i.e., non-overlapping compute/communication), broken down by GPU time spent on EMB lookups, compute (GEMM), all-to-all communication (A2A), and other miscellaneous operations (e.g., all-reduce and reduce-scatter).

First, we observe that RecD halves exposed A2A communication across all RMs. A2A is a significant component of each training iteration. RecD significantly improves training throughput by reducing the amount of over-the-network bytes via IKJTs. Thus one reason for RM1’s larger training throughput gains is because it exposes more communication by using more sequence features that RecD optimizes for.

The second reason is because RM1 uses expensive transformers to pool EMB activations for several user sequence features; RecD deduplicated the compute for these transformers by grouping each transformer’s features together using IKJTs. This is evidenced by an additional reduction (12% of iteration latency) in the amount of time spent in GEMMs for RM1. Meanwhile, RM2 and RM3 saw slight increases in exposed GEMM time. This is because less of it was hidden as RecD reduced A2A latencies, as well as a slight increase due to the additional index.Select.

We also observe a small improvement across RMs due to faster EMB lookups (1 – 2% of iteration latency) by eliminating redundant lookups. While this did not significantly improve trainer throughput given the same batch size, using fewer EMB activations allowed us to increase batch size to improve trainer throughput, as we study next.

Finally, Figure 8 shows why translating DedupeFactor to throughput gains is challenging. RM1 and RM2 used the same table and features with similar DedupeFactors.
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Table 2. Breakdown of trainer throughput (QPS) and efficiency for \( RM_1 \) with RecD, enabling larger batches and complex models.

| Config          | Norm. QPS | Max Mem. Util. | Avg. Mem. Util. | Norm. Comp. Efficiency (flop/s/GPU) |
|-----------------|-----------|----------------|-----------------|-----------------------------------|
| Baseline        | 1.00      | 99.90          | 72.83           | 1.00                              |
| RecD            | 1.89      | 27.76          | 22.20           | 1.73                              |
| RecD + EMB D256 | 1.55      | 40.87          | 31.17           | 1.92                              |
| RecD + B6144    | 2.26      | 91.78          | 51.55           | 2.12                              |

However, RecD reduced \( RM_1 \)’s iteration time by 44% compared to 23% for \( RM_2 \) due to the differences in model architectures and exposed compute/communication cycles as discussed above. We discuss observations on how ML engineers choose which features to deduplicate in Section 7.

Ablation Study. To understand how specific optimizations contribute to training throughput, we performed an ablation study using \( RM_1 \) as shown in Figure 9. First, simply using clustered tables provides no training throughput benefit. While clustering is necessary for RecD, it is not sufficient alone since KJTs still contain duplicate feature values. By using IKJTs (and jagged index select) to deduplicate EMB lookups and activations, we could increase batch size to 4096 and realized a 1.34× gain to training throughput. We then used multiple IKJT groups, which further allowed us to deduplicate the compute required by expensive transformers, which led to a 2.42× increase in throughput. Finally, this further allowed us to increase batch size to 6144, which resulted in a final 2.48× increase in training throughput.

Trainer Resource Utilization. Because RecD reduces GPU resource requirements, we can also tune model hyperparameters in order to further improve model throughput and accuracy. To illustrate this, Table 2 shows the throughput, memory utilization, and GPU compute efficiency for \( RM_1 \) as we enabled RecD. Using a baseline batch size of 2048 required the entirety of GPU memory. RecD reduced the maximum and average memory utilization from 99.9% to 27.76% and 72.83% to 22.2%, respectively. This allowed our memory headroom to devote to EMBs or larger batches to improve model accuracy or training throughput, respectively. For example, we were able to increase EMB dimensions from 128 to 256 or batch size from 2048 to 6144. Furthermore, Table 2 shows how RecD improves the utilization of GPU compute by increasing realized GPU FLOPS to 2.12× the baseline. GPU streaming multiprocessors can achieve higher utilization because they spend less time waiting for exposed A2A communication due to smaller IKJTs.

Single-node Training. While RecD greatly increased distributed training throughput, we also evaluated RecD’s benefit for single-node training. To do so, we downsized \( RM_1 \) to fit within a single ZionEX training node and launched a training job with and without RecD. We observed a 2.18× throughput increase in the single-node training setup by using RecD. RecD still benefits single-node training because it targets GPU memory, network, and compute resources (Section 5). While single-node training reduces the amount of exposed communication due to high-bandwidth NVLink interconnects, RecD still improves compute and memory efficiency, leading to improved training throughput. Since storage and readers are disaggregated, RecD’s benefits are the same for single-node training as shown in Figure 7.

Impacts to Accuracy. RecD itself largely does not affect model accuracy. Specifically, IKJTs encode the exact same logical data as KJTs and thus trainers can train on the exact same batches. The only RecD optimization that affects model accuracy is clustering tables by session ID. In fact, clustering leads to significant improvements in accuracy. This is because without clustering, duplicate examples from a session are distributed across batches. The model sees each user’s data only once, reducing the chance of overfitting less popular sparse feature values.

6.3 Why does RecD improve reader throughput?

Figure 7 also showed how RecD also improved the throughput of each reader, allowing us to provision fewer readers to feed trainers. To understand why, Figure 10 shows a breakdown of reader CPU compute time spent on filling,
converting and processing each sample, normalized to the baseline. For each RM, reader time is largely spent on fills: fetching data from Tectonic and decrypting, decompressing (zstd), and decoding bytes to form rows. As shown in Table 3, by clustering tables, RecD allows each reader to read significantly fewer bytes per sample. Readers need to spend on both reading and extracting data, reducing the CPU time spent on fills by 50%, 33%, and 46% for RM1, RM2, and RM3, respectively. Furthermore, RecD can also reduce the CPU time required for processing, since preprocessing operations take deduplicated IKJTs as input. RM1 and RM2 required 13% and 11% less time for processing, while RM3 was effectively the same (3% increase).

RecD requires additional compute at readers to detect duplicate values (via hashing) during feature conversion. Fortunately, Figure 10 shows that this overhead is largely negligible. While the feature conversion time increased by 21%, 37%, and 11% for RM1, RM2, and RM3, respectively, feature conversion requires a small amount of overall compute. Thus, the overall overhead of conversion is negligible (1%) and is easily offset by fill and process benefits.

6.4 Summary

Table 4 summarizes a breakdown of the impacts of each optimization presented in Table 1 for the end-to-end training pipeline performance of RM1, as reported in our evaluation results. RecD presents a suite of optimizations where not only does each optimization yield direct benefits at its respective pipeline system (e.g., storage, readers, or trainers), but it also enables further downstream optimizations. O1 (sharding) and O2 (clustering) directly improve storage efficiency and reader throughput, but they also increase the opportunity for O3 (IKJTs) to deduplicate features. While O3 introduces slight reader overheads, these are nullified by O4, and both O3 and O4 enable trainer-side optimizations. These trainer-side optimizations (O5-O7) ultimately lead to a 2.48x training throughput, as reported in Section 6.2. Collectively, RecD optimizations benefit the end-to-end DLRM training pipeline, including storage, readers, and trainers.

7 DISCUSSION

Deciding Which Features to Deduplicate. ML engineers typically apply heuristics to decide which features to deduplicate. IKJTs introduce no trainer overheads aside from an additional index select used to convert IKJTs to KJTs. Thus, the benefit of deduplicating a feature f must at least offset this overhead. While the specific “worth it” DedupeFactor(f) threshold varies from model-to-model (due to model architecture differences illustrated in Section 6.2), ML engineers will typically start by deduplicating features with DedupeFactor(f) > 1.5, and apply standard hyper parameter tuning techniques based on observed trainer throughput to finalize the deduplicated feature set.

Boosting Dedupe Factors. DedupeFactor(f) increases as a function of S, the average number of samples per session. While Section 3 showed that S = 16.5 for the characterized industry-scale dataset, we are exploring methods to increase S to yield benefits across the end-to-end training pipeline. For example, the current data generation pipeline downsamples (i.e., discards) training samples to keep datasets at a manageable size. However, downsampling is applied on a per-sample basis. By downsampling at a per-session basis, we can further increase S, increasing DedupeFactor without affecting model accuracy.

Alternative Solutions and Generality. We considered alternative designs to exploit the session-centric characteristic of DLRM datasets. One promising avenue was to explicitly deduplicate samples within the table schema itself. Specifically, each user session requests inferences (one for each impression) in batches, and each batch uses the same features guaranteeing exact matches. Instead of generating a table row for each impression, we considered generating
We decided against this approach for several reasons. First, there would still be many duplicates as feature values are largely static even across inference batches. Secondly, we use a common dataset schema across DLRMs to ensure interoperability and developer velocity across models and datasets — introducing a new schema would require significant engineering and adoption effort across multiple services. RecD is transparent to the training infrastructure because it does not require schema changes, and it enables even more deduplication across request batches.

Furthermore, RecD optimizations are easily generalized to different environments, supporting myriad table schemas and model architectures. Enabling RecD reader and trainer optimizations only requires a feature converter module to convert arbitrary table schemas into the IKJT encoding, and an index select call to convert IKJTs back to KJTs when necessary. Because IKJTs directly build on standardized jagged tensors (ragged tensors in TensorFlow (TensorFlow, 2022)), preprocessing functions and model architectures can operate on IKJTs as KJTs with minimal changes.

Supporting Partial IKJTs. Supporting exact matches captures the vast majority of duplication in industry-scale datasets — 81.6% of an estimated 93.9% maximum (Section 3). Even so, IKJTs are also easily extended to support partial deduplication, capturing an additional 7.8% of values, by leveraging the fact that partial matches are shifts. Partial IKJTs remove the offsets slice, and instead encode each row’s [offset, length] in the inverse_lookup slice. In the example in Figure 5, feature b can by partially deduplicated via a partial IKJT consisting of values = [3, 4, 5, 6] and inverse_lookup = [[0, 3], [1, 3], [0, 3]].

8 Related Work

Duplication in DLRM Datasets. Gai et al. notes how DLRM datasets at Alibaba exhibits feature duplication (Gai et al., 2017). To exploit this, the authors mention a “common feature trick” that routes samples from similar users to the same worker in a parameter server training setup. The authors speed up training throughput by caching and reusing the parameter update for “common” features across each worker’s samples. Follow-up work by Ge et al. cites using the “common feature trick” during training (Ge et al., 2018). Unfortunately, the authors provide scant details on how “common” features are generated, stored, or encoded. They also do not elucidate how model architectures can exploit duplicate features, nor how the “common feature trick” can extend beyond parameter servers to synchronous training used in scale-out GPU training clusters (Mudigere et al., 2022). We provide an in-depth characterization of feature value duplication in industrial DLRM datasets. RecD deduplicates features across the end-to-end training pipeline by coalescing duplicate features in storage, compactly encoding them into IKJTs, and intelligently training on IKJTs.

Deduplication in ML. Data deduplication has been studied in ML training outside of DLRMs. Lee et al. studied how deduplication in a text corpus improved model accuracy for language tasks (Lee et al., 2022). Allamanis studied how duplication in code datasets degraded model performance for ML models for source code (Allamanis, 2019). To the best of our knowledge, our work is the first to study the systems implications of duplication in ML training datasets.

Database Systems. Data deduplication is a well-studied area in databases. IKJTs use a similar encoding mechanism to dictionary encoding commonly used in file formats such as Parquet (Apache, 2022). To coalesce duplicates within an IKJT, we rely on cluster by clauses supported by myriad database execution engines, such as Spark (Zaharia et al., 2012). RecD applies these concepts to enable and encode deduplicated tensors for ML training jobs.

Systems Optimizations for DLRM Training. Zhao et al. presented various optimizations to improve DSI efficiency for DLRM training at Meta (Zhao et al., 2022). RecShard (Sethi et al., 2022) and Adnan et al. (Adnan et al., 2021) leveraged skewed feature popularities to shard EMBs across GPUs, improving training throughput. Similarly, Fleche (Xie et al., 2022) is an embedding cache that caches EMBs on GPU HBM while relying on CPU DRAM for holding entire EMBs, targeting only single-GPU training. To avoid cache write conflicts, Fleche recognizes that many sparse feature IDs are duplicated within a batch and performs only a single cache lookup for each unique ID, similar to RecD’s ability to deduplicate EMB lookups. TT-Rec (Yin et al., 2021) demonstrated compression techniques for EMBs. RecD provides orthogonal optimizations to improve storage, reading, and training performance by deduplicating features across the DLRM training pipeline.

9 Conclusion

This paper presented RecD, a suite of optimizations for industry-scale, end-to-end DLRM training pipelines. We provide an in-depth characterization of how DLRM datasets exhibit inherent feature duplication. RecD coalesces duplicate features within a training batch, efficiently encodes them using IKJTs, and optimizes DLRM model architectures to train on deduplicated tensors. As a result, RecD improves training and preprocessing throughput and storage efficiency by up to 2.48×, 1.79×, and 3.71×, respectively.
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