# Deep Lake: a Lakehouse for Deep Learning

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#### ABSTRACT

Traditional data lakes provide critical data infrastructure for analytical workloads by enabling time travel, running SQL queries, ingesting data with ACID transactions, and visualizing petabyte-scale datasets on cloud storage. They allow organizations to break down data silos, unlock data-driven decision-making, improve operational efficiency, and reduce costs. However, as deep learning takes over common analytical workflows, traditional data lakes become less useful for applications such as natural language processing (NLP), audio processing, computer vision, and applications involving non-tabular datasets.

This paper presents Deep Lake, an open-source lakehouse for deep learning applications developed at Activeloop<sup>12</sup>. Deep Lake maintains the benefits of a vanilla data lake with one key difference: it stores complex data, such as images, videos, annotations, as well as tabular data, in the form of tensors and rapidly streams the data over the network to (a) Tensor Query Language, (b) in-browser visualization engine, or (c) deep learning frameworks without sacrificing GPU utilization. Datasets stored in Deep Lake can be accessed from PyTorch[53], TensorFlow[23], JAX[29], and integrate with numerous MLOps tools.

# **KEYWORDS**

Deep Lake, Deep Learning, Data Lake, Lakehouse, Cloud Computing, Distributed Systems

# 1 INTRODUCTION

A data lake is a central repository that allows organizations to store structured, unstructured, and semi-structured data in one place. Data lakes provide a better way to manage, govern, and analyze data. In addition, they provide a way to break data silos and gain insights previously hidden in disparate data sources. First-generation data lakes traditionally collected data into distributed storage systems such as HDFS [66] or AWS S3[1]. Unorganized collections of the data turned data lakes into "data swamps", which gave rise to the second generation data lakes led by Delta, Iceberg, and Hudi [10, 15, 25]. They strictly operate on top of standardized structured formats such as Parquet, ORC, Avro [6, 20, 74] and provide features like time travel, ACID transactions, and schema evolution. Data lakes directly integrate with query engines such as Presto, Athena, Hive, Photon [12, 61, 65, 71] to run analytical queries. Additionally, they connect to frameworks like Hadoop, Spark, and Airflow [9, 14, 77] for ETL pipelines maintenance. In its turn, the integration between data lakes and query engines with clear compute and storage separation resulted in the emergence of systems like Lakehouse [26] that

serve as an alternative to data warehouses, including Snowflake, BigQuery, Redshift, and Clickhouse[2, 4, 31, 37].

Over the past decade, deep learning has outpaced traditional machine learning techniques involving unstructured and complex data such as text, images, videos, and audio [28, 35, 41, 44, 48, 51, 58, 78]. Not only did deep learning systems outgrow traditional techniques, but they also achieved super-human accuracy in applications such as cancer detection from X-Ray images, anatomical reconstruction of human neural cells, playing games, driving cars, unfolding proteins, and generating images [39, 45, 56, 67, 72]. Large language models with transformer based architectures achieved state-of-theart results across translation, reasoning, summarization, and text completion tasks [30, 34, 73, 76]. Large multi-modal networks embed unstructured data into vectors for cross-modal search [27, 55]. Moreover, they are used to generate photo-realistic images from text [57, 60]. Although one of the primary contributors to the success of deep learning models has been the availability of large datasets such as CoCo (330K images), ImageNet (1.2M images), Oscar (multilingual text corpus), and LAION (400M and 5B images) [32, 46, 63, 69], it does not have a well-established data infrastructure blueprint similar to traditional analytical workloads to support such scale. On the other hand, Modern Data Stack (MDS) lacks features required to deploy performant deep learning-based solutions, so organizations opt to develop in-house systems.

In this paper, we introduce Deep Lake, a lakehouse specialized for deep learning workloads. Deep Lake retains the benefits of a traditional data lake with one notable distinction: it stores complex data, such as images, videos, annotations, and tabular data, as tensors and rapidly streams the data to deep learning frameworks over the network without sacrificing GPU utilization. Furthermore, it provides native interoperability between deep learning frameworks such as PyTorch, TensorFlow, and JAX [23, 29, 53].

The remainder of this paper unfolds as follows. We begin by considering current challenges in deep learning on unstructured data. Next, we present the Deep Lake storage format with its key concepts. Furthermore, we discuss Deep Lake capabilities and its applications within the ML cycle. Next, we provide performance experiments and discuss the results. Finally, we review related work, list possible limitations, and conclude.

#### 2 CURRENT CHALLENGES

In this section, we discuss the current and historical challenges of unstructured or complex data management.

# 2.1 Complex Data Types in a Databases

There are three widely accepted reasons why blobs or binary data such as images should not be stored in a database. Firstly, databases

<sup>&</sup>lt;sup>1</sup>Source code available: https://github.com/activeloopai/deeplake

<sup>&</sup>lt;sup>2</sup>Documentation available at https://docs.deeplake.ai

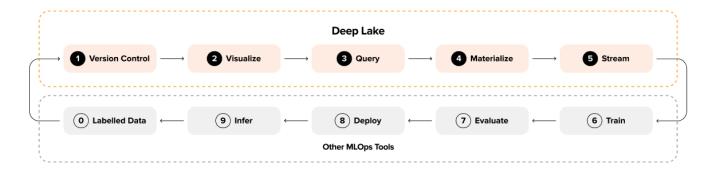


Figure 1: Machine Learning Loop with Deep Lake

typically operate on row-wise storage architecture. Therefore, running a query becomes significantly slower if a row contains large amounts of data. Secondly, persisting data in hot memory is expensive compared to cold storage. Lastly, storing images in a RAM can quickly outgrow in-memory capacity and potentially cause a database to fail. In effect, this renders most widely-used data infrastructure tools unsuitable for processing unstructured and complex data types - due to speed, cost, and reliability concerns.

# 2.2 Complex Data Along with Tabular Formats

Increases in large-scale analytical and BI workloads motivated the development of compressed structured formats like Parquet, ORC, Avro, or transient in-memory formats like Arrow[6, 13, 20, 74]. As tabular formats gained adoption, attempts to extend those formats, such as Petastorm [18] or Feather [7]for deep learning, have emerged. To the best of our knowledge, these formats have yet to gain wide adoption. This approach primarily benefits from native integrations with Modern Data Stack (MDS). However, as discussed previously, upstream tools require fundamental modifications to adapt to deep learning applications.

# 2.3 Object Storage for Deep Learning

The current cloud-native choice for storing large unstructured datasets is object storage such as AWS S3[1], Google Cloud Storage (GCS)[3] or MinIO[17]. Object storage does offer three main benefits over distributed network file systems. They are (a) cost-efficient, (b) scalable, and (c) serve as a format-agnostic repository. However, cloud storages are not without drawbacks. Firstly, they introduce significant latency overhead, especially when iterating over many small files such as text or JSON. Next, unstructured data ingestion without metadata control can produce "data swamps". Furthermore, object storage has built-in version control; it is rarely used in data science workflows. Lastly, data on object storage gets copied to a virtual machine before training, thus resulting in storage overhead and additional costs.

### 2.4 Second Generation of Data Lakes

The second generation data lakes led by Delta, Iceberg, Hudi [10, 15, 25] overcome limitations of object storage by managing tabular format files with the following primary properties.

- Update operations: inserting or deleting a row on top of a tabular format file.
- (2) Streaming: downstream data ingestion with ACID properties and upstream integration with query engine exposing SQL interface
- (3) Schema evolution: evolving columnar structure while preserving backward compatibility.
- (4) Time travel and audit log trailing: preserving historical state with rollback property where queries can be reproducible. Also, support for row-level control on data lineage.
- (5) Layout optimization: Built-in feature to optimize file sizes and data compaction with custom ordering support. Significantly speeds up querying.

However, second-generation data lakes are still bound by the limitations of the inherent data formats to be used in deep learning, as previously discussed in section 2.2. Hence in this paper, we extend the second generation of data lake capabilities for deep learning use cases by rethinking the format and upstream features, including querying, visualization, and native integration to deep learning frameworks.

# 3 DEEP LAKE STORAGE FORMAT

Deep Lake datasets follow columnar storage architecture, with tensors as columns, as shown in Fig. 2. Each tensor is a collection of *chunks* - binary blobs that contain the data samples. An index map associated with each tensor helps find the right chunk and index of the sample within that chunk for a given sample index.

#### 3.1 Dataset

A sample in a dataset represents a single row indexed across parallel tensors. As opposed to a document storage format, sample elements are logically independent, which enables partial access to samples for running performant queries or streaming selected tensors over the network to the GPU training instances. Multiple tensors can be grouped. Groups implement syntactic nesting and define how tensors are related to each other. Syntactic nesting avoids the format complication for hierarchical memory layout. Changes to the dataset's schema are also tracked over time with version control, similar to dataset content changes.

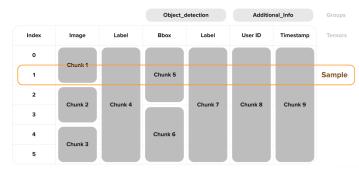


Figure 2: How each sample (row) is stored in a set of columnar tensors with dynamically sized chunks

#### 3.2 Tensors

Tensors are typed and can be appended or in-place modified. Default access to an index or a set of indices returns the data as NumPy arrays[50]. Instead of storing 1-D data as seen in Parquet [74] or series in Arrow[13], tensors can accommodate n-dimensional data, where typically the first dimension corresponds to the index or batch dimension. Tensors can contain dynamically shaped arrays, also called ragged tensors, as opposed to other statically chunked array formats such as Zarr [49].

# 3.3 Types

Htype defines the expectations on samples in a tensor such as data type (dtype as seen in NumPy[50]), shape, number of dimensions, or compression. Typed tensors make interacting with deep learning frameworks straightforward and enable sanity checks and efficient memory layout. By inheriting from a generic tensor htype, we can construct types such as image, video, audio, bbox, dicom, and others. For example, a tensor with image htype would expect samples being appended to it to have dtype as uint8 and shape length 3 (i.e. width, height and number of channels). We further expand on the notion of htypes allowing for meta types that support storing image sequences in tensors (sequence[image]), referencing to remotely stored images, while maintaining the regular behavior of a image tensor (link[image]), or even possible cross-format support.

# 3.4 Memory Layout

Tensors are stored in chunks at the storage level. While statically (inferred) shaped chunking avoids maintaining a chunk map table, it introduces significant user overhead during the specification of the tensor, custom compression usage limitations, underutilized storage for dynamically shaped tensors, and post-processing inefficiencies. Deep Lake chunks are constructed based on the lower and upper bound of the chunk size to fit a limited number of samples. This comes with a trade-off of having a compressed index map that preserves the sample index to chunk id mapping per tensor while enabling chunk sizes in the range optimal for streaming while accommodating mixed shape samples. One could consider the approach taken in this paper as an optimized trade-off between file system page map and compute-defined map-less array storage system. For practical reasons, a single chunk encoder can be scaled

to billions of images while maintaining a 150MB chunk encoder per 1PB tensor data. Further scaling can be introduced by sharding the chunk encoder. Chunks contain header information such as byte ranges, shapes of the samples, and the sample data itself. If a sample is larger than the upper bound chunk size, which is the case for large aerial or microscopy images, the sample is tiled into chunks across spatial dimensions. The only exception to tiling is videos. Videos are preserved due to efficient frame mapping to indices, only key-frame decompression, and range-based requests while streaming.

# 3.5 Access Patterns

Deep Lake storage format is optimized for deep learning training and inference, including sequential and random access. Sequential access is used for running scan queries, transforming tensors into other tensors, or running inference. Random access use cases include multiple annotators writing labels to the same image or models storing back predictions along with the dataset. While the strict mode is disabled, out-of-the-bounds indices of a tensor can be assigned, thus accommodating sparse tensors. However, random assignment over time will produce inefficiently stored data chunks. To fix the data layout, we implement an on-the-fly re-chunking algorithm to optimize the data layout. One of the key access patterns of Deep Lake is shuffled stream access for training machine learning models. It requires random or custom order access while streaming chunks into the training process. This is achieved by involving range-based requests to access sub-elements inside chunks, running complex queries before training to determine the order, and maintaining a buffer cache of fetched and unutilized data. This avoids having a separate compute cluster for running shuffling algorithm [47].

#### 3.6 Storage Providers

Deep Lake can be plugged into any storage provider, including object storages such as AWS S3[1], Google Cloud Storage (GCS)[3], POSIX compatible file systems or local in-memory storage. Moreover, it constructs memory caching by chaining various storage providers together, for instance - Least Recently Used (LRU) cache of remote S3 storage with local in-memory data.

# 4 DEEP LAKE SYSTEM OVERVIEW

#### 4.1 Version Control

Deep Lake also addresses the need for reproducibility of experiments and compliance, with a complete data lineage. Different versions of the dataset exist in the same storage, separated by subdirectories. Each sub-directory acts as an independent dataset with its individual metadata files. Unlike a non-versioned dataset, these sub-directories only contain chunks modified in the particular version, along with a corresponding chunk\_set per tensor containing the names of all the modified chunks. A version control info file present at the root of the directory keeps track of the relationship between these versions as a branching version-control tree. While accessing any chunk of a tensor at a particular version, the version control tree is traversed starting from the current commit, heading towards the first commit. During the traversal, the chunk set of each version is checked for the existence of the required chunk. If

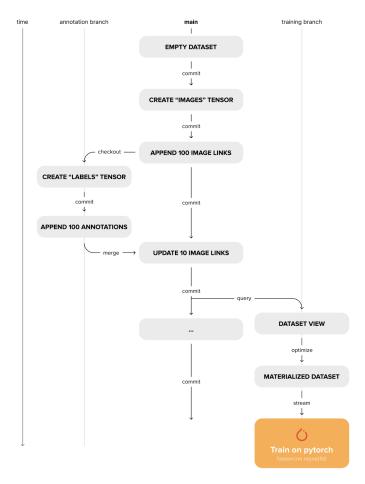


Figure 3: Version History of Evolving Deep Lake Dataset

the chunk is found, the traversal is stopped, and data is retrieved. For keeping track of differences across versions, for each version, a commit diff file is also stored per tensor. This makes it faster to compare across versions and branches. Moreover, ids of samples are generated and stored during dataset population. This is important for keeping track of the same samples during merge operations. Deep Lake's version control interface is the Python API, which enables machine learning engineers to version their datasets within their data processing scripts without switching back and forth from the CLI. It supports the following commands:

- Commit: creates an immutable snapshot of the current state of the dataset.
- Checkout: checks out to an existing branch/commit or creates a new branch if one doesn't exist.
- Diff: compares the differences between 2 versions of the dataset.
- Merge: merges two different versions of the dataset, resolving conflicts according to the policy defined by the user.

#### 4.2 Visualization of Tensors

Data visualization is a crucial part of ML workflows, especially when the data is hard to parse analytically. Fast and seamless visualization allows faster data collection, annotation, quality inspection, and training iterations. The Deep Lake visualizer engine provides a web interface for visualizing large-scale data directly from the source. It considers htype of the tensors to determine the best layout for visualization. Primary tensors, such as image, video and audio are displayed first, while secondary data and annotations, such as text, class\_label, bbox and binary\_mask are overlayed. The visualizer also considers the meta type information, such as sequence to provide a sequential view of the data, where sequences can be played and jump to the specific position of the sequence without fetching the whole data, which is relevant for video or audio use cases. Visualizer addresses critical needs in ML workflows, enabling users to understand and troubleshoot the data, depict its evolution, compare predictions to ground truth, or display multiple sequences of images (e.g. camera images and disparity maps) side-by-side.

# 4.3 Tensor Query Language

Querying and balancing datasets is a common step in training deep learning workflows. Typically, this is achieved inside a dataloader using sampling strategies or separate pre-processing step to subselect the dataset. On the other hand, traditional data lakes connect to external analytical query engines [61] and stream Dataframes to data science workflows. To resolve the gap between the format and fast access to the specific data, we provide an embedded SQL-like query engine implemented in C++ called Tensor Query Language (TQL). We parse SQL query into a computational graph of tensor operations, provide the query plan to the scheduler and execute the query. Execution of the query can be delegated to external tensor computation frameworks such as PyTorch [53] or XLA [59] and efficiently utilization underlying accelerated hardware. In addition to standard SQL features, TQL also implements numeric computation. There are two main reasons for implementing a new query language. First, traditional SQL does not support multidimensional array operations such as computing mean of the image pixels or projecting arrays on a specific dimension. TQL solves this by adding Python/NumPy style indexing, slicing of arrays, and providing large set of convenience functions to work with arrays, many of which are common operations supported in NumPy. Second, TQL enables a deeper integration of the query with other features of the Deep Lake, such as version control, streaming engine, and visualization. For example, TQL allows querying data on the specific versions or potentially across multiple versions of a dataset. TQL also supports specific instructions to customize visualization of the query result or seamless integration with the dataloader for filtered streaming. Embedded query engine runs along with the client either while training a model on a remote compute instance or in-browser compiled over WebAssembly. TQL extends SQL with numeric computations on top of multi-dimensional columns. It constructs views of datasets, which can be visualized or directly streamed to deep learning frameworks. Query views, however can be sparse, which can affect streaming performance.

```
SELECT
  images[100:500, 100:500, 0:2] as crop,
  NORMALIZE(
    boxes,
    [100, 100, 400, 400]) as box
FROM
  dataset
WHERE IOU(boxes, "training/boxes") > 0.95
ORDER BY IOU(boxes, "training/boxes")
ARRANGE BY labels
```

Figure 4: An example query that arranges cropped images ordered by bounding boxes predictions error measured over user-defined function IOU (Intersection over Union).

#### 4.4 Materialization

Most of the raw data used for deep learning is stored as raw files (compressed in formats like JPEG), either locally or on the cloud. A common way to construct datasets is to preserve pointers to these raw files in a database, query this to get the required subset of data, fetch the filtered files to a machine, and then train a model iterating over files. In addition, data lineage needs to be manually maintained with a provenance file. Deep Lake format simplifies these steps using linked tensors - storing pointers (links/urls to one or multiple cloud providers) to the original data. The pointers within a single tensor can be connected to multiple storage providers, thus allowing users to get a consolidated view of their data present in multiple sources. All of Deep Lake's features including queries, version control and streaming to deep learning frameworks can be used with linked tensors. However, the performance of data streaming will not be as optimal as default tensors. A similar problem exists with sparse views created due to queries, which would be inefficiently streamed due to the chunk layout.Furthermore, materialization transforms the dataset view into an optimal layout to stream into deep learning frameworks to iterate faster. Materialization involves fetching the actual data from links or views, and efficiently laying out into chunks. Performing this step towards the end of machine learning workflows leads to minimum data duplication, while ensuring ensures optimal streaming performance and minimal data duplication, with full data lineage.

# 4.5 Streaming Dataloader

As datasets become larger, storing and transferring over network from a remote distributed storage becomes inevitable. Data streaming enables training models without waiting for all of the data to be copied to a local machine. The streaming dataloader ensures data fetching, decompression, applying transformations, collation, and data handover to the training model. Deep learning data-loaders typically delegate fetching and transformation to parallel running processes to avoid synchronous computation. Then the data is transferred to the main worker through inter-process communication (IPC) which introduces memory copy overhead or using shared memory with some reliability issues. In contrast, Deep Lake dataloader delegates highly parallel fetching and in-place decompressing in C++ per process to avoid global interpreter lock. Then, it passes the in-memory pointer to user-defined transformation

function and collates them before exposing to the training loop in deep learning native memory layout. Transformation concurrently executes in parallel when it uses only native library routines calls and release python global interpreter lock (GIL) accordingly. As a result, we get:

- *Performance*: Delivering data to the deep learning model fast enough so that either the GPU is fully utilized or bottlenecked by the compute.
- Smart Scheduler: Dynamically differentiating between CPU-intensive jobs prioritization over less-intensive.
- Efficient Resource Allocation: Predicting memory consumption to avoid breaking the training process due to memory overfilling.

# 5 USE CASES

In this section, we review the applications of Deep Lake in various use cases.

# 5.1 Machine Learning Use Cases

- 5.1.1 Deep Learning Model Training. Deep learning models are trained at multiple levels in an organization, ranging from exploratory training occurring on personal computers to large-scale training that occurring on distributed machines involving many GPUs. The time and effort required to bring the data from long-term storage to the training client is often comparable to the training itself. Deep Lake solves this problem by enabling rapid streaming of data without bottlenecking the downstream training process, thus avoiding the cost and time required to duplicate data on local storage.
- 5.1.2 Data Lineage and Version Control. Deep learning data constantly evolves as new data is added and existing data is quality controlled. Analytical and training workloads occur in parallel while the data is changing. Hence, knowing which data version was used by a given workload is critical to understand the relationship between the data and model performance. Deep Lake enables deep learning practitioners to understand which version of their data was used in any analytical workload and to time travel across these versions if an audit is required. Since all data is mutable, it can be edited to meet compliance-related privacy requirements. Like Git for code, Deep Lake also introduces the concept of data branches, allowing experimentation and editing of data without affecting colleagues' work.
- 5.1.3 Data Querying and Analytics. Training of deep learning models rarely occurs on all data collected by an organization for a particular application. Training datasets are often constructed by filtering the raw data based on conditions increasing model performance, which often includes data balancing, eliminating redundant data, or selecting data that contains specific features. Deep Lake provides the tools to query and analyze data so that deep learning engineers can create datasets yielding the highest accuracy models.
- 5.1.4 Data Inspection and Quality Control. Though unsupervised learning is becoming more applicable in real-world use cases, most deep learning applications still rely on supervised learning. Any supervised learning system is only as good as the quality of its data,

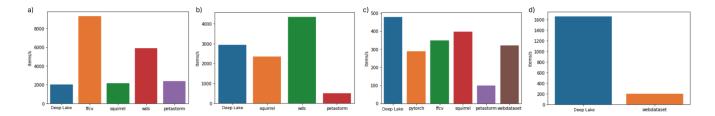


Figure 5: Conversion of raw CIFAR (30x30) images on the filesystem to the corresponding data formats where Deep Lake is comparable to Petastorm (Parquet extension). b) iterate over all the samples in CIFAR (30x30) once stored in the corresponding format c) local iteration of the random images dataset d) remote dataloader iteration of random image dataset

often achieved by manual and exhaustive inspection of the data. Since this process is time-consuming, it is critical to provide the humans in the loop with tools to examine vast amounts of data very quickly. Deep Lake allows to inspect deep learning datasets of any size from the browser without any setup time or need to download data. Furthermore, the tools can be extended for comparing model results with ground truth. Combined with querying and version control, this can be applied to the iterative improvement of data to achieve the best possible model.

#### **6 PERFORMANCE BENCHMARKS**

In this section, we experimentally demonstrate Deep Lake's state-ofthe-art performance at scale, against other dataloaders, and contrast using Deep Lake to an object storage.

# 6.1 Comparison with Other Dataloaders

All experiments shown in Fig. 5 were carried out on p3.2xlarge EC2 instance on AWS with one V100 GPU card. The datasets used were the CIFAR-10 dataset and the random dataset. CIFAR-10 consists of colored images with size (30x30) stored in raw JPEG file with the labels stored in the corresponding TXT files. The random dataset is a generated dataset consisting of colored (250x250) images stored as JPEG files. The number of images in both the datasets were 50,000. The list of libraries in which the benchmarks were carried out were Hub, FFCV [36], Squirrel [70], Webdataset [19] and Petastorm [18]. For more detailed dataloader benchmarks, we would recommend an exhaustive datalaoder overview study by Ofeidis et al. (forthcoming) [40].

# 6.2 Streamable Training on the Cloud

6.2.1 Single GPU training on ImageNet compared to cloud storage. We take ImageNet dataset [33] and store it on AWS S3 [1] as original and Deep Lake format. The dataset contains 1.2 million images and labels in total 150GB. Deep Lake achieves virtually similar training performance as if the data was local to the machine. This saves up to 4x GPU compute time and cost as shown in Fig. 6

6.2.2 Distributed training of a large multi-modal dataset. As a second experiment, we take LAION dataset [62] containing 400M image-text pairs and train CLIP [55], image-text embedding model with 1 billion parameters. The original dataset is a table of Parquet files with a column of image URLs. Fetching the data using the LAION toolkit takes 100 hours and only 6 hours to ingest into Deep

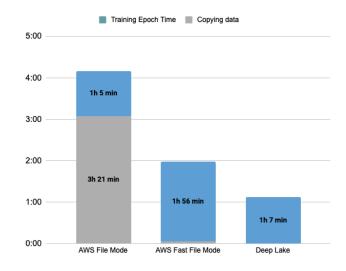


Figure 6: Training on ImageNet on an S3: AWS File Mode copies file by file from S3; Fast File Mode starts immediately with slower training; Deep Lake performs as if data is local, although it is streamed

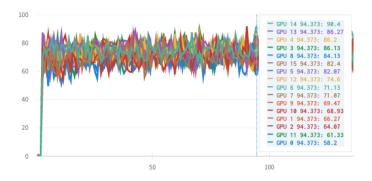


Figure 7: GPU Utilization of 16xA100 GPUs on the same machine while training 1B parameter CLIP model on LAION-400M streaming the dataset from us-east to us-central.

Lake dataset on S3. The dataset download from the source took 100 hours, while ingestion to Deep Lake format took only 6 hours,

totaling 1.9TB in size. The dataset has been stored on AWS in the US-east region while training GPU machine in the US-central region. As shown on Fig. 7 Deep Lake achieves high GPU utilization by streaming 5,100 images/s into 16 Nvidia A100 GPUs while without model up to 80,000 images/s per machine on the same region.

# 7 DISCUSSION AND LIMITATIONS

Deep Lake's primary use cases include (a) Deep Learning Model Training, (b) Data Lineage and Version Control, (c) Data Querying, and Analytics, (d) Data Inspection and Quality Control. Deep Lake achieves state-of-the-art results in local and remote settings, as seen in benchmarks for iterating on large images. Primarily, it has been faster than FFCV [36], which claimed a reduction of ImageNet model training up to 98 cents per model training. Furthermore, Deep Lake achieves similar ingestion performance to Petastorm [18] (referred to extended Parquet). Although the iteration on smaller images is faster on Petastorm, Deep Lake significantly outperforms on larger images. Parquet is optimized for small cells and analytical workloads, while Deep Lake is optimized for large, dynamically shaped tensorial data. Compared to other data lake solutions, its minimal python package design enables Deep Lake to be easily integrated into large-scale distributed training or inference workloads. The current implementation of Deep Lake has opportunities for further improvement. Firstly, the storage format does not support custom ordering for an even more efficient storage layout required for vector search or key-value indexing. Secondly, Deep Lake implements branch-based locks for concurrent access. Similar to Delta ACID transaction model [25], Deep Lake can be extended to highly-performant parallel workloads. Thirdly, the current implementation of TQL only supports a subset of SQL operations (i.e., does not support operations such as join). Further work will focus on making it SQL-complete, extending to more numeric operations, and benchmarking against SQL engines.

# 8 RELATED WORK

Deep Lake builds on numerous prominent contributions across Academia and industry. For example, Tensor Query Language, similar to TQP [38] and Velox [54] approaches, runs n-dimensional numeric operations on tensor storage by truly leveraging the full capabilities of deep learning frameworks. Multiple projects have tried to improve upon or create new formats for storing unstructured datasets including TFRecord extending Protobuf [5], Petastorm [18] extending Parquet [74], Feather[7] extending arrow[13], Squirrel using MessagePack [70], Beton in FFCV [36]. Designing a universal dataset format that solves all use cases is very challenging. Our approach was mostly inspired by CloudVolume[11], a 4-D chunked NumPy storage for storing large volumetric biomedical data. There are other similar chunked NumPy array storage formats such as Zarr [49], TensorStore[22], TileDB[52]. Furthermore, Deep Lake introduced a typing system, dynamically shaped tensors, integration with fast deep learning streaming data loaders, and in-browser visualization support. An alternative approach to store large-scale datasets is to use HPC distributed file system such as Lustre [64], extending with PyTorch cache [42] or performant storage layer such as AIStore[24]. Deep Lake datasets can be stored on top of POSIX

or REST API-compatible distributed storage systems by leveraging their benefits. Other comparable approaches evolve in vector databases [8, 75, 75] for storing embeddings, feature stores [16, 68] or data version control systems such as DVC [43], or LakeFS[21]. In contrast, Deep Lake version control is in-built into the format without an external dependency, including Git. Overall, Deep Lake takes an example from data lakes such as Hudi, Iceberg, Delta [10, 15, 25] and complements Databarick's Lakehouse [26] for Deep Learning applications.

# 9 CONCLUSION

We presented Deep Lake, the lakehouse for deep learning. Deep Lake is designed to help deep learning workflows run as seamlessly as analytical workflows run on MDS. Notably, Deep Lake is built to retain prominent features of data lakes, such as time travel, querying, and rapid data ingestion at scale. One important distinction from traditional data lakes is Deep Lake's ability to store unstructured data with all its metadata in deep learning-native columnar format, which enables rapid data streaming. This allows materializing data subsets on-the-fly, visualizing them in-browser, or ingesting them into deep learning frameworks without sacrificing GPU utilization. Finally, we show that Deep Lake achieves state-of-the-art performance for deep learning on large datasets via multiple benchmarks.

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