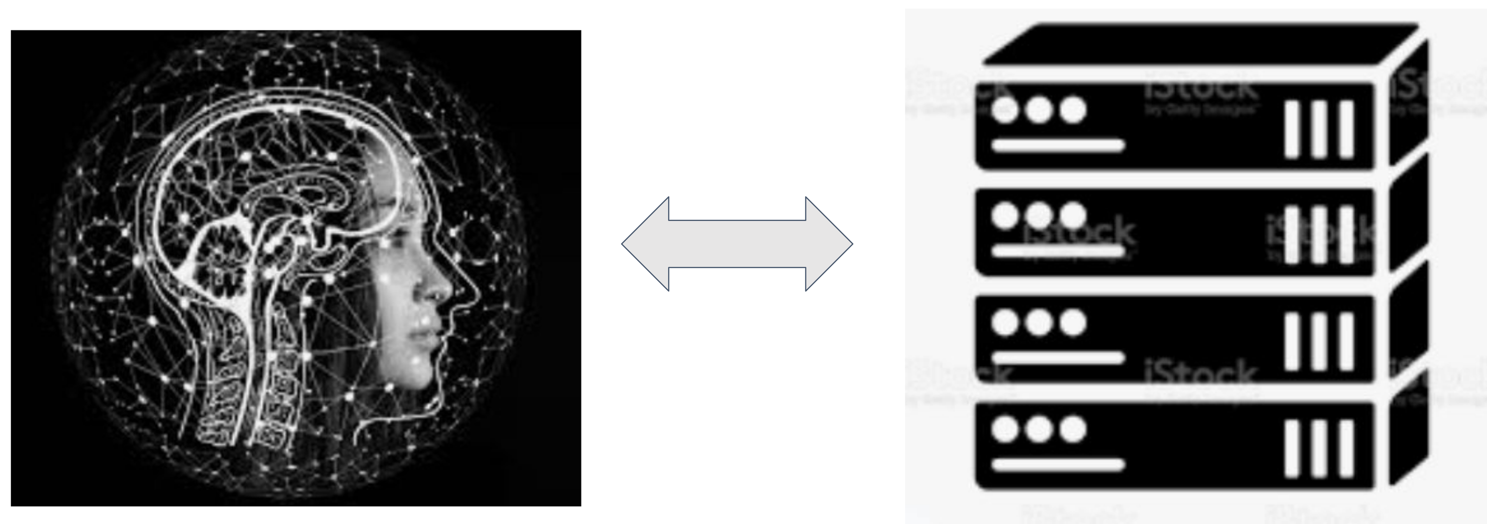
Storage Benchmarking with Deep Learning Workloads

Peng Cheng

Introduction



- In this AI-driven era, while computer infrastructure is often the focus, **storage** is equally important.
- Loading the dataset is the basic step in model training.
- Trend of **decoupled storage and compute** in datacenters.
  - Cost
  - Scalability
  - Availability

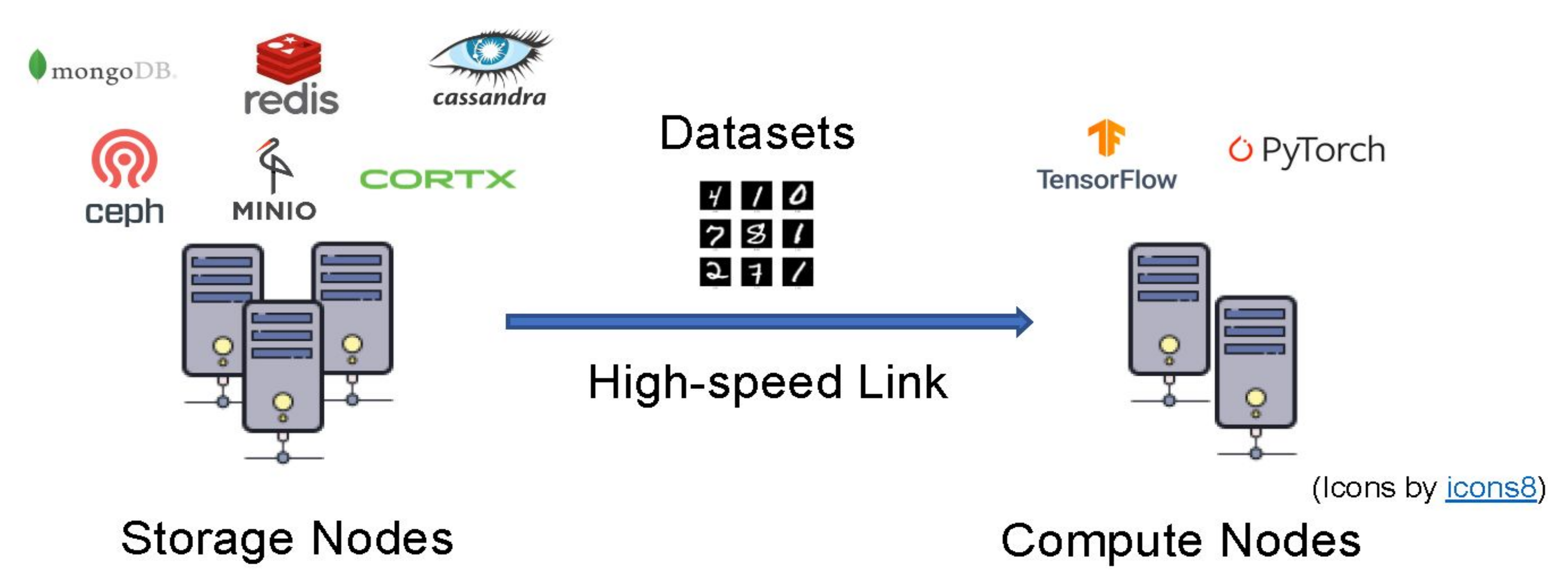
Motivation:

Explore the optimal storage system and data format to store DL data and the underlying trade-offs in it.

Storage Systems

- **Key-Value Databases**
  - A more traditional storage solution that only provides limited metadata.
- **Object Storage**
  - Each object contains:
    - Data (binary file)
    - Object ID
    - Metadata that describes the data
  - More scalable: stored in flat hierarchy
  - More searchable: extensible metadata.

Methodology



Overivew

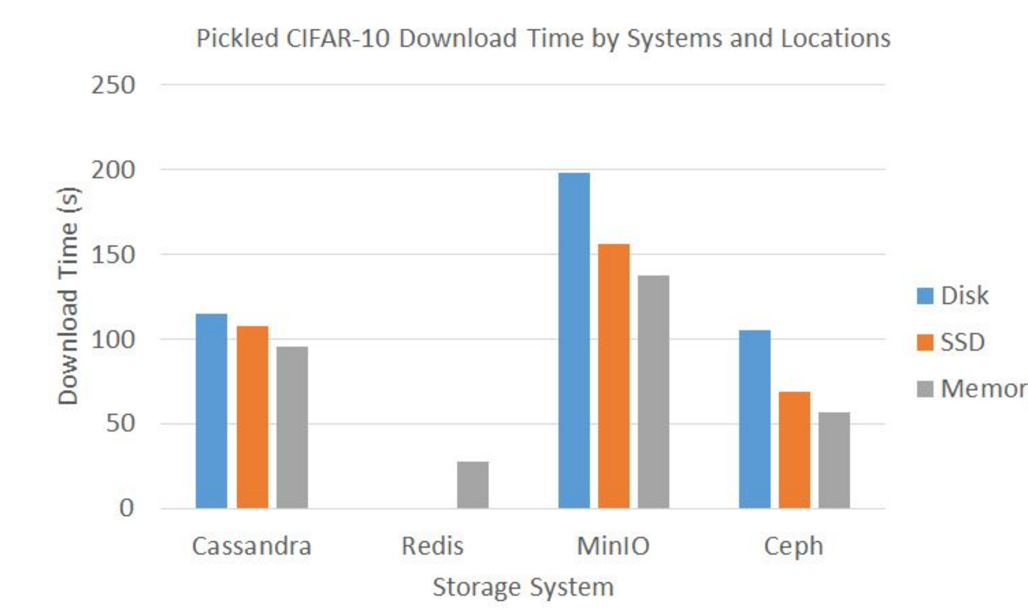
- **Storage Disaggregation for DL**
  - We parsed datasets raw files and stored each image with its label as a single object.
- **Decoupled Storage and Compute**
  - Objects are stored in different systems in storage nodes.
  - The client download them in different batch sizes.

Experiment Setup

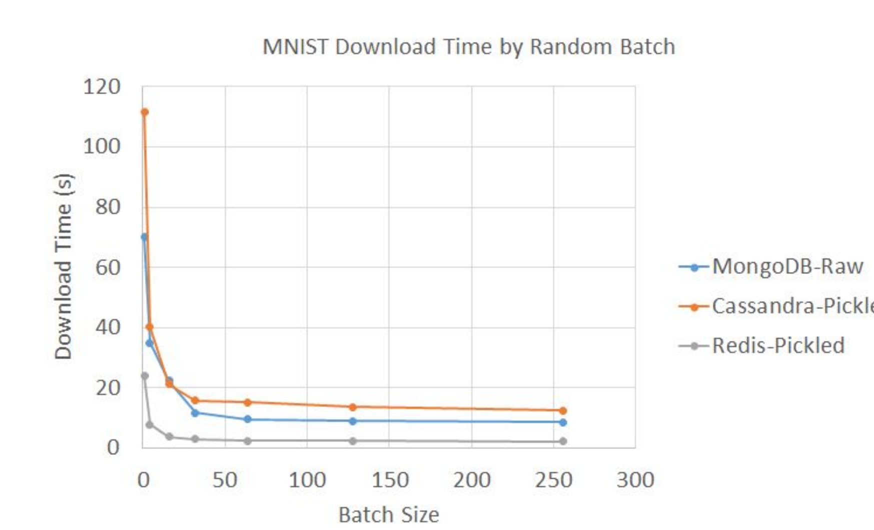
- **Storage Systems:**
  - **Key-Value Databases:** Cassandra, Redis, MongoDB
  - **Object Storage Systems:** MinIO, Ceph
- **Testbed:** d430 nodes @ Emulab
- **Network**: LAN with 1Gbps link speed
- **Datasets:**
  - **MNIST (236 MB):** 60,000 images of handwritten digits
  - **CIFAR-10 (952 MB):** 60,000 32 *32 images in 10 classes
- **Location:** memory, disk, SSD
- **Access pattern**: single, batch size, full batch object(s)
- **Data Format:** raw, blob, pickled
- **Storage Disaggregation Granularity**

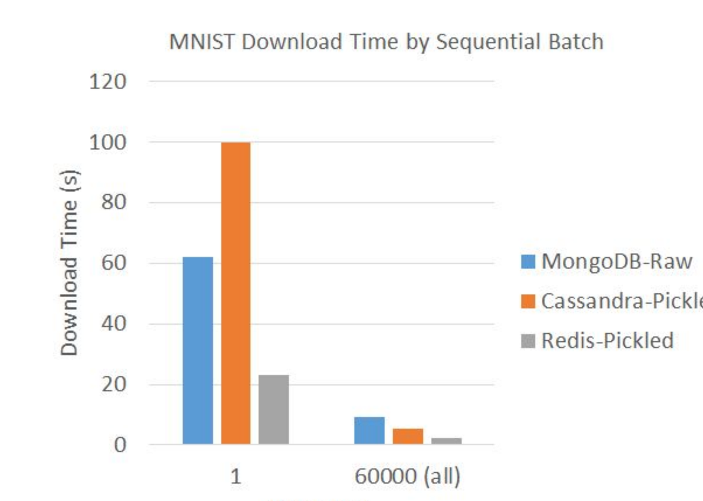
Selected Results

- **System choice matters, memory > SSD > disk.**



- **Download time decreases as batch size increases.**





- **Data format influences space used in storage systems.**