Object Storage
for
Deep Learning Frameworks

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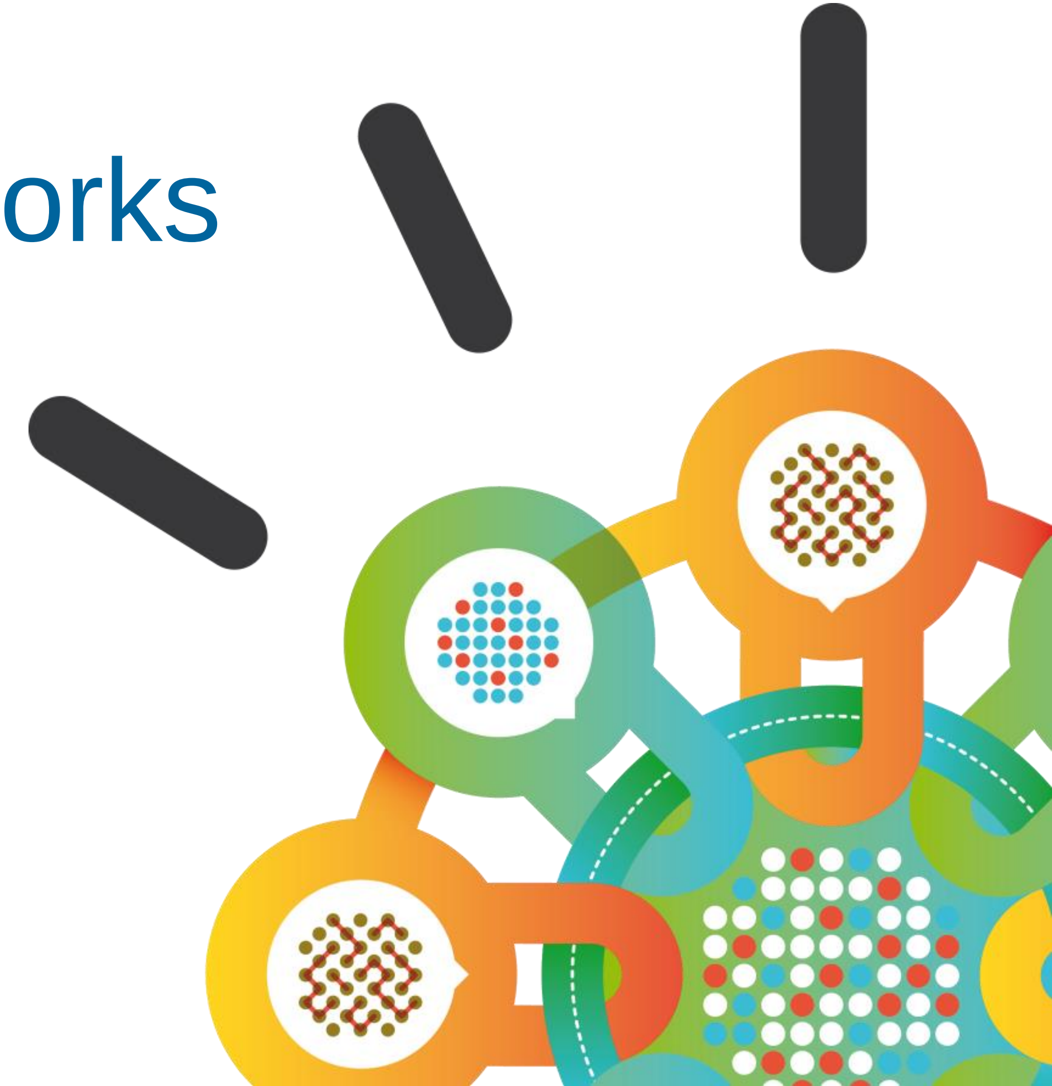
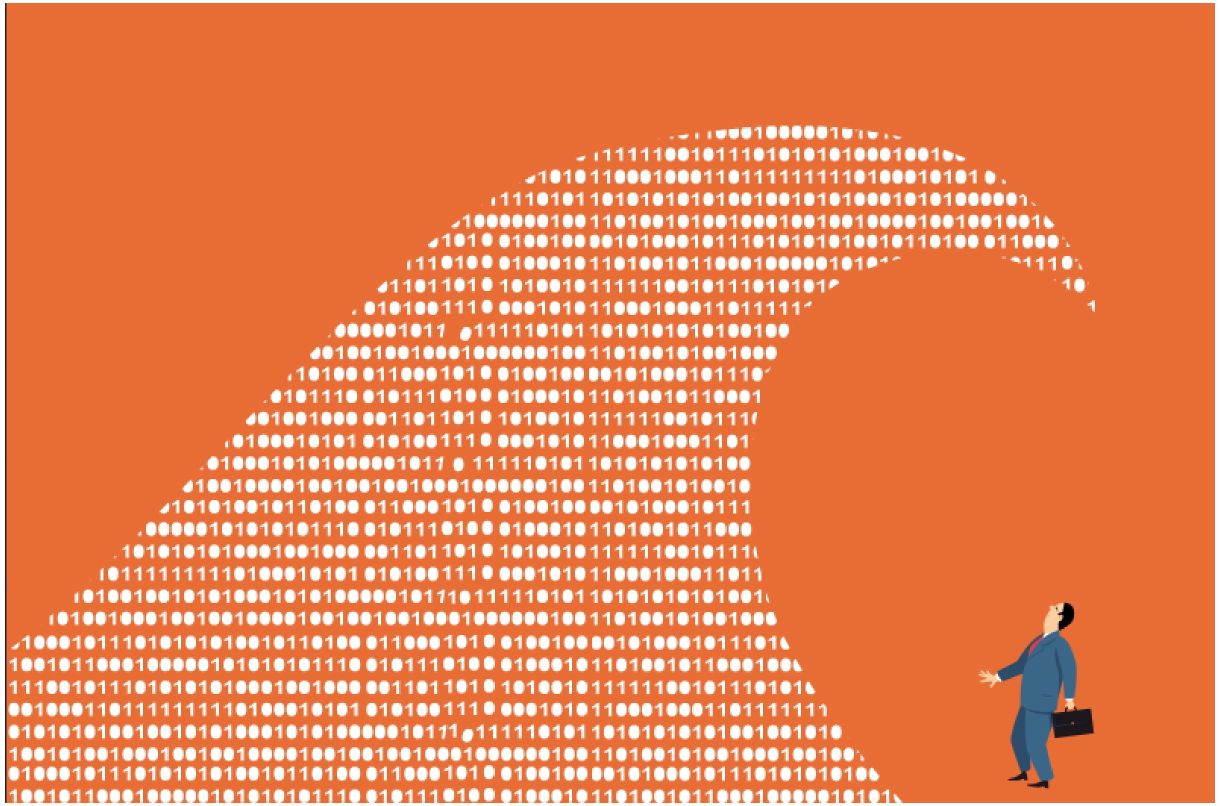


Background

- Machine learning are quickly becoming the disruptive technology of the decade
  - Fueled by the explosion in:
    1) Big data
    2) High-speed accelerators such as GPUs, FPGAs, and Tensor Processing Units
    3) Advancement of training algorithms and architectures

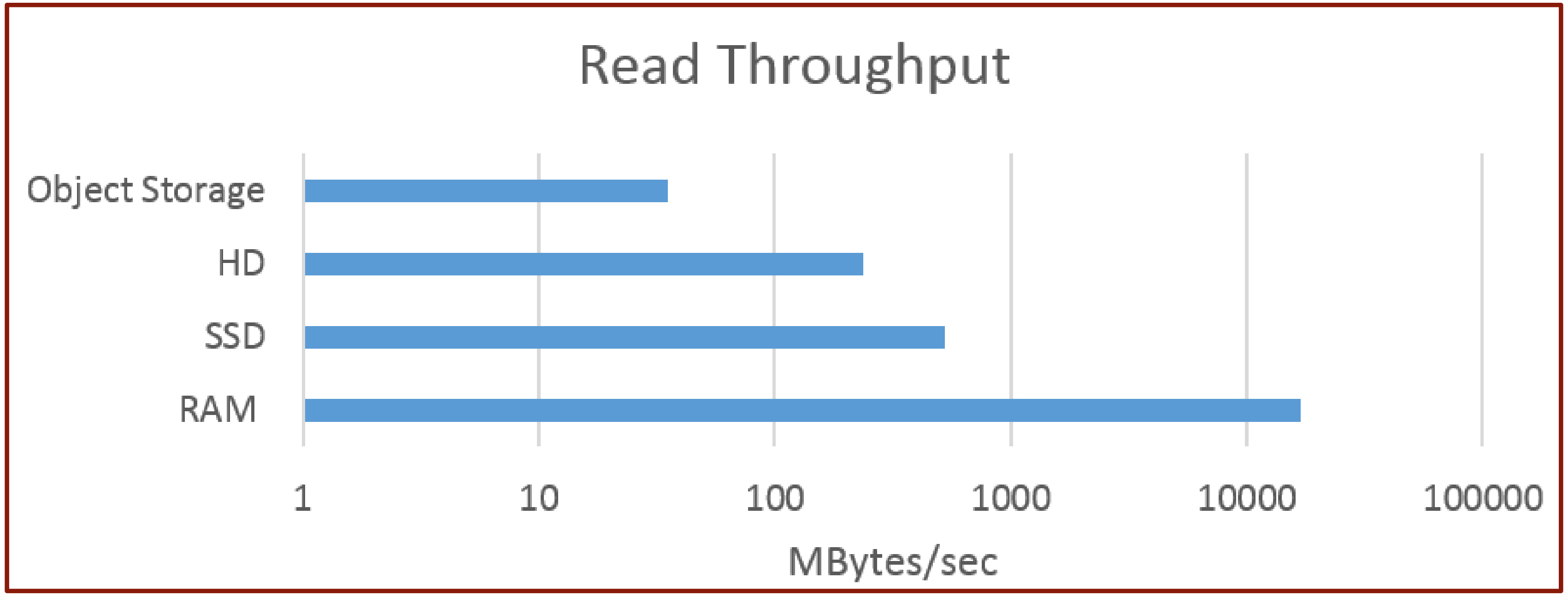


- In order to feed GPUs with data at the required high throughput, deep learning systems traditionally:
  - Use a POSIX file system interface
  - Keep the data locally on the same machine as the GPUs
- However, this model does not scale with the number of users, the volume of data, and the variety of workloads

Problem statement

- To handle all this big data, object storage has become a storage model of choice offering
  - disaggregated storage
  - high scalability
  - low cost
  - extremely high durability

- But its performance characteristics have traditionally been a barrier for analytics and machine learning workloads



- In this talk we explore how to run high throughput analytics on data that resides in inexpensive object storage without the need to pre-load or stage the data

How much throughput is good enough?

Given

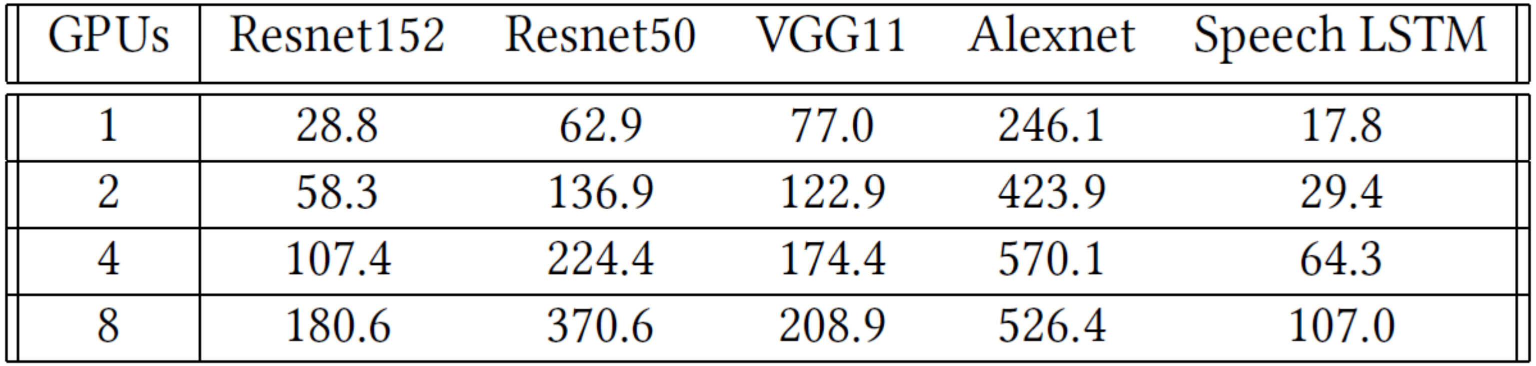
- Most of the heavy work in machine learning is done by the GPUs
- With some GPUs selling for over $10K, they are often the most expensive component in a deep learning system

Therefore

- We aim to provide throughput that is sufficient to keep the GPUs busy 100% of the time

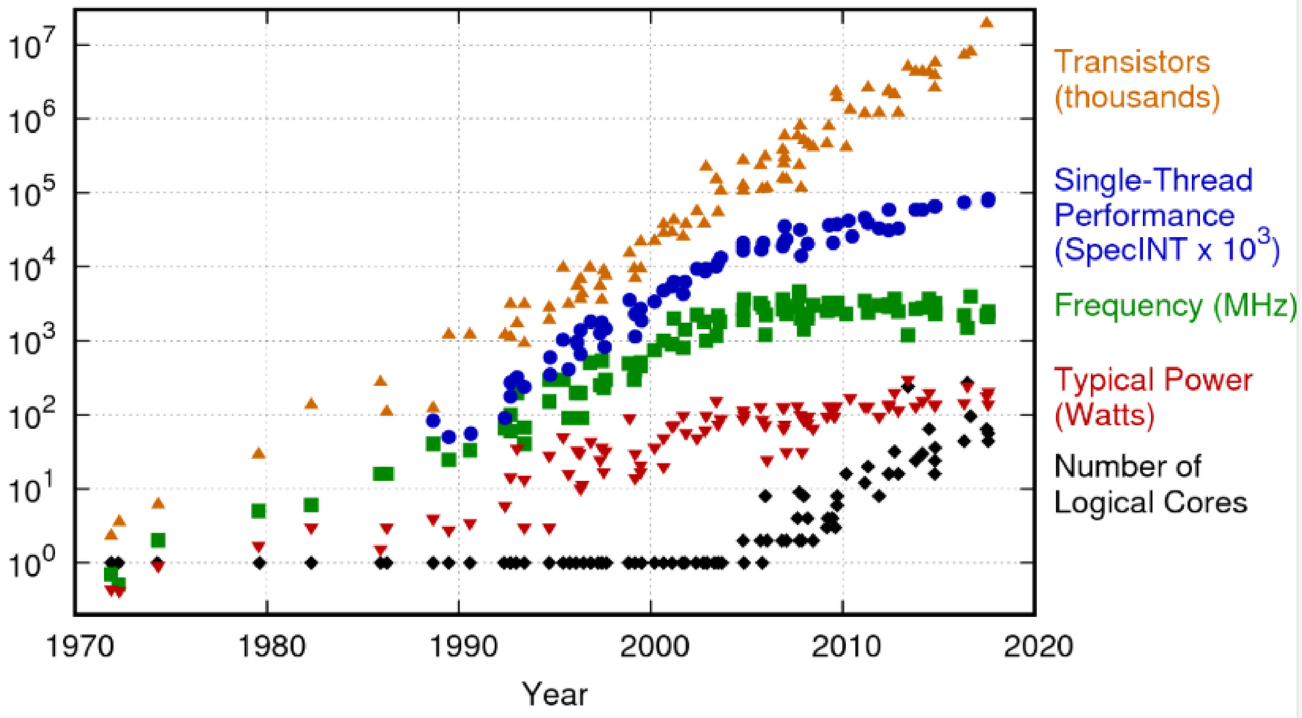
Keeping up with the GPUs

- Storage Bandwidth (MB/s) of popular deep learning workloads running with varying number of Nvidia Volta V100 GPUs →



GPUs	Resnet152	Resnet50	VGG11	Alexnet	Speech LSTM
1	28.8	62.9	77.0	246.1	17.8
2	58.3	136.9	122.9	423.9	29.4
4	107.4	224.4	174.4	570.1	64.3
8	180.6	370.6	208.9	526.4	107.0

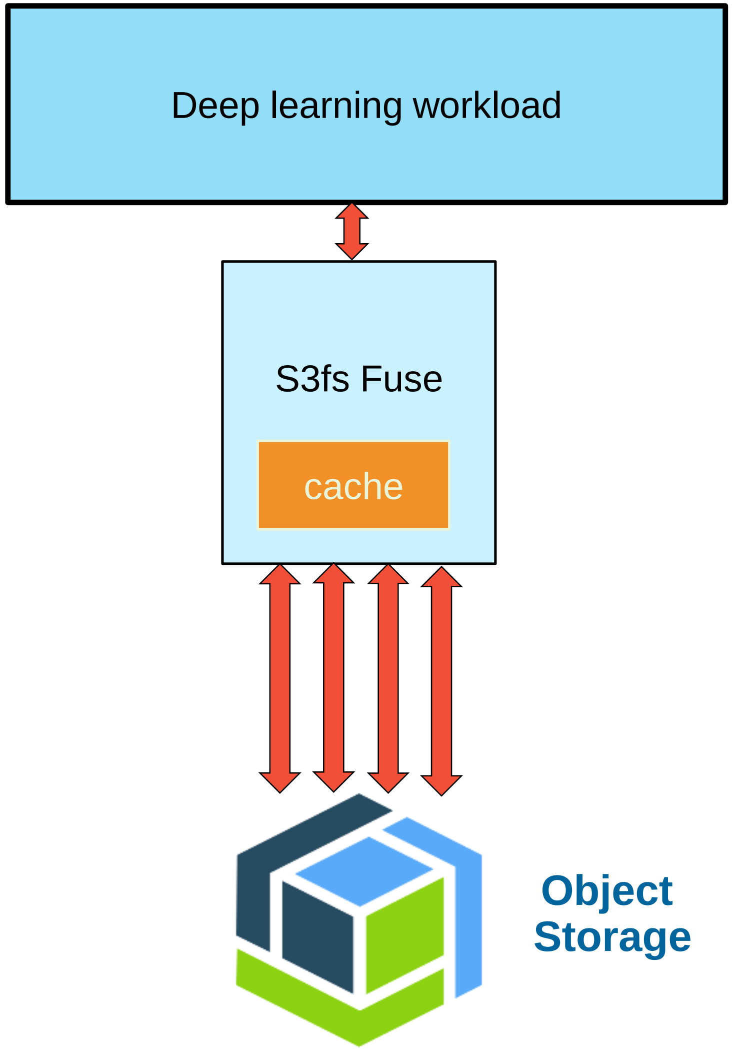
- Microprocessor trend data →
- CPUs are currently advancing at a rate of about 1.1x performance improvement per year
- GPUs are advancing at a rate of about 1.5x per year or 10x performance improvement every 5 to 6 years
- Can we expect machine learning workload to consume 5000MB/s+ in 2024?



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2017 by K. Rupp

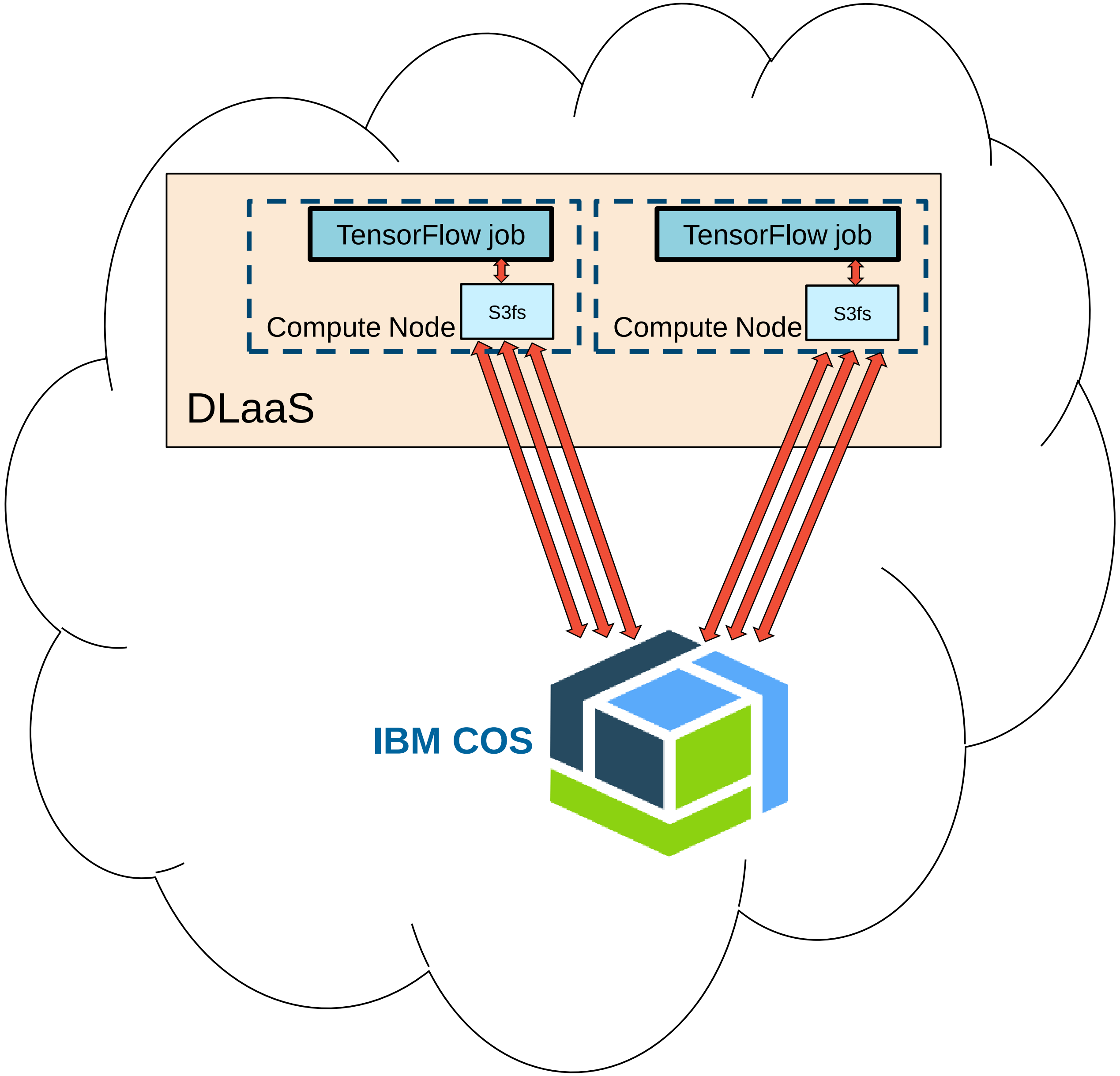
Architecture

- Support existing deep learning workloads without modifications
- Keep the training data on inexpensive object storage
- Store the training results (logs and model weights) in object storage
- Enable deep learning workload to continue using POSIX interface
- Supply data faster than object store single connection speeds
- Support prefetching and optimize traffic
- Leverage a local in-memory cache
  - Reduce network transfer for multi-epoch training
  - Increase throughput and reduce latency



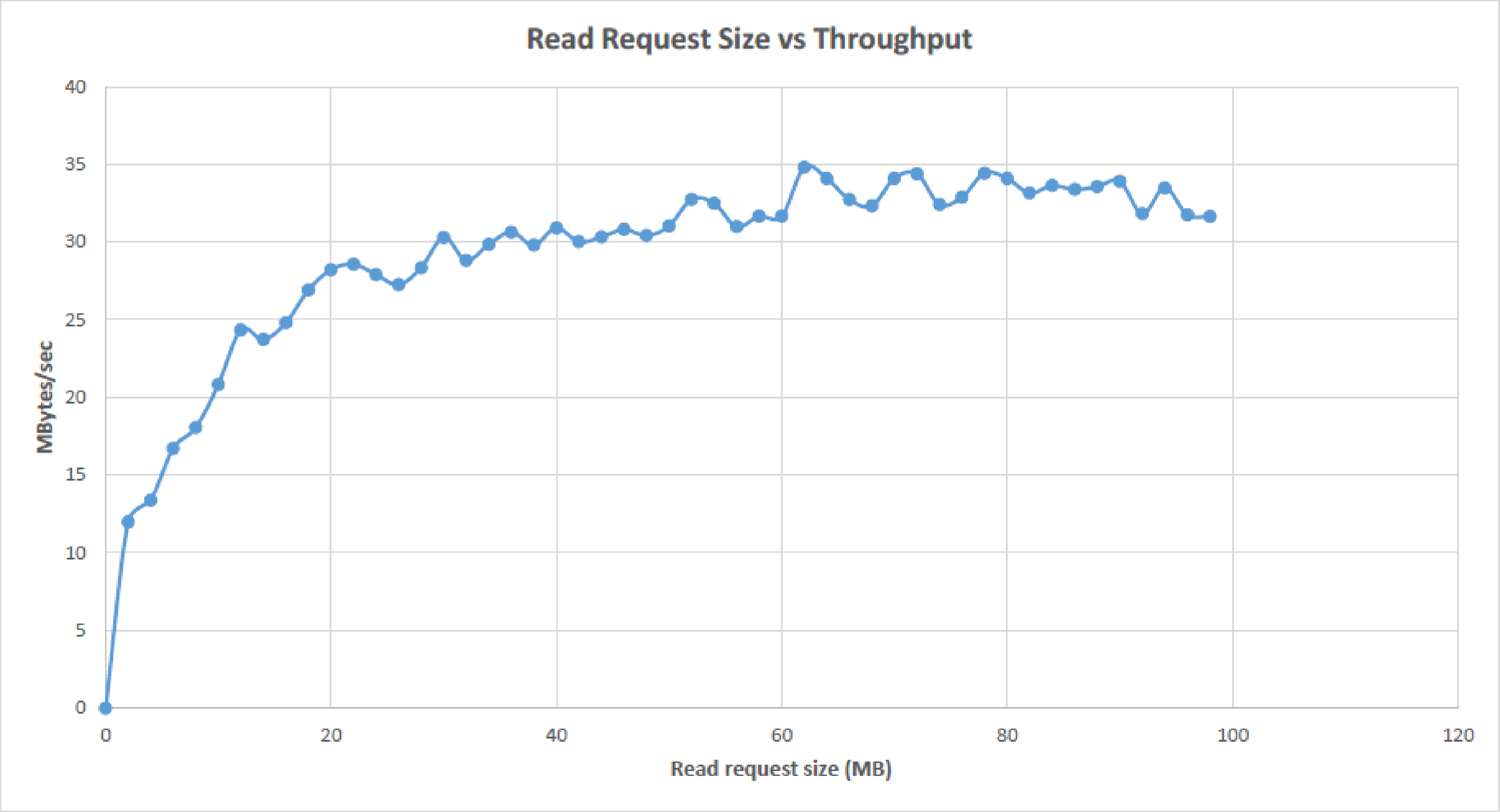
Single vs multi threaded reads

- Single threaded performance is well below the last network link bandwidth
- Driven by the multi user, multi tenant, distributed nature of object storage
- When a client requests multiple requests, an object storage can easily saturate his or her network
- We therefore convert read requests into multiple concurrent requests
- This allows us to sustain local disk like throughputs (550MBytes/sec) for single object read



Reading in chunks

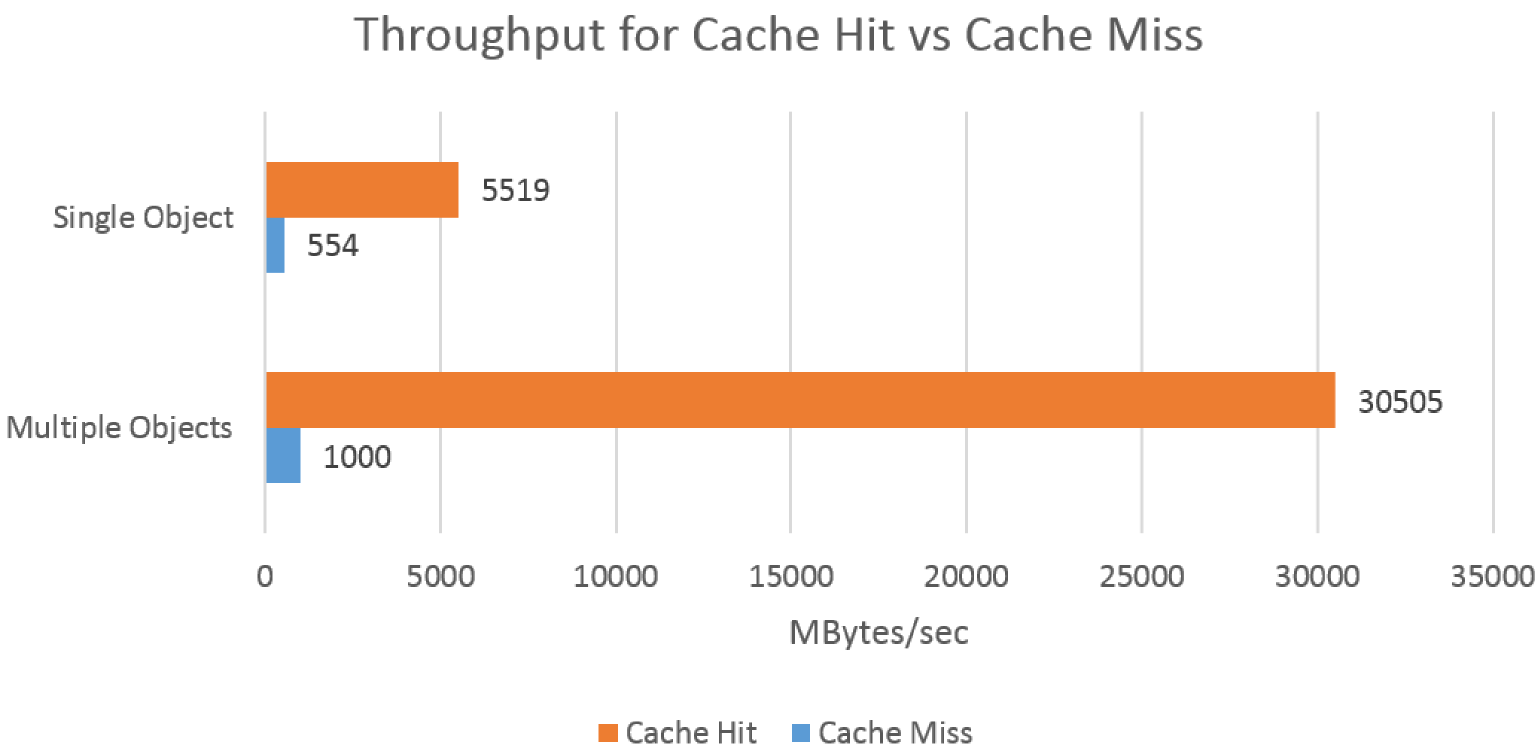
- We read data in chunks rather than read the precise amount that the client requests
- A larger chunk size enables a ‘poor man’s read ahead prefetching’
- A smaller chunk size enables additional concurrent reads



- We choose chunk size of 52 MB
- Why 52 MB?
  - – Optimal chunk size for our environment is around 50MB
  - – Our object storage best practices suggest using range read requests that are multiples of 4 MB

In-memory cache

- We have deployed an in-memory cache using the Linux kernel page cache
- collocated with the compute nodes
- Caching both
  - – data chunks
  - – meta data
- Since deep learning frameworks often run their training in multiple epochs this results in substantial speed improvement as long as the data fits within the cache

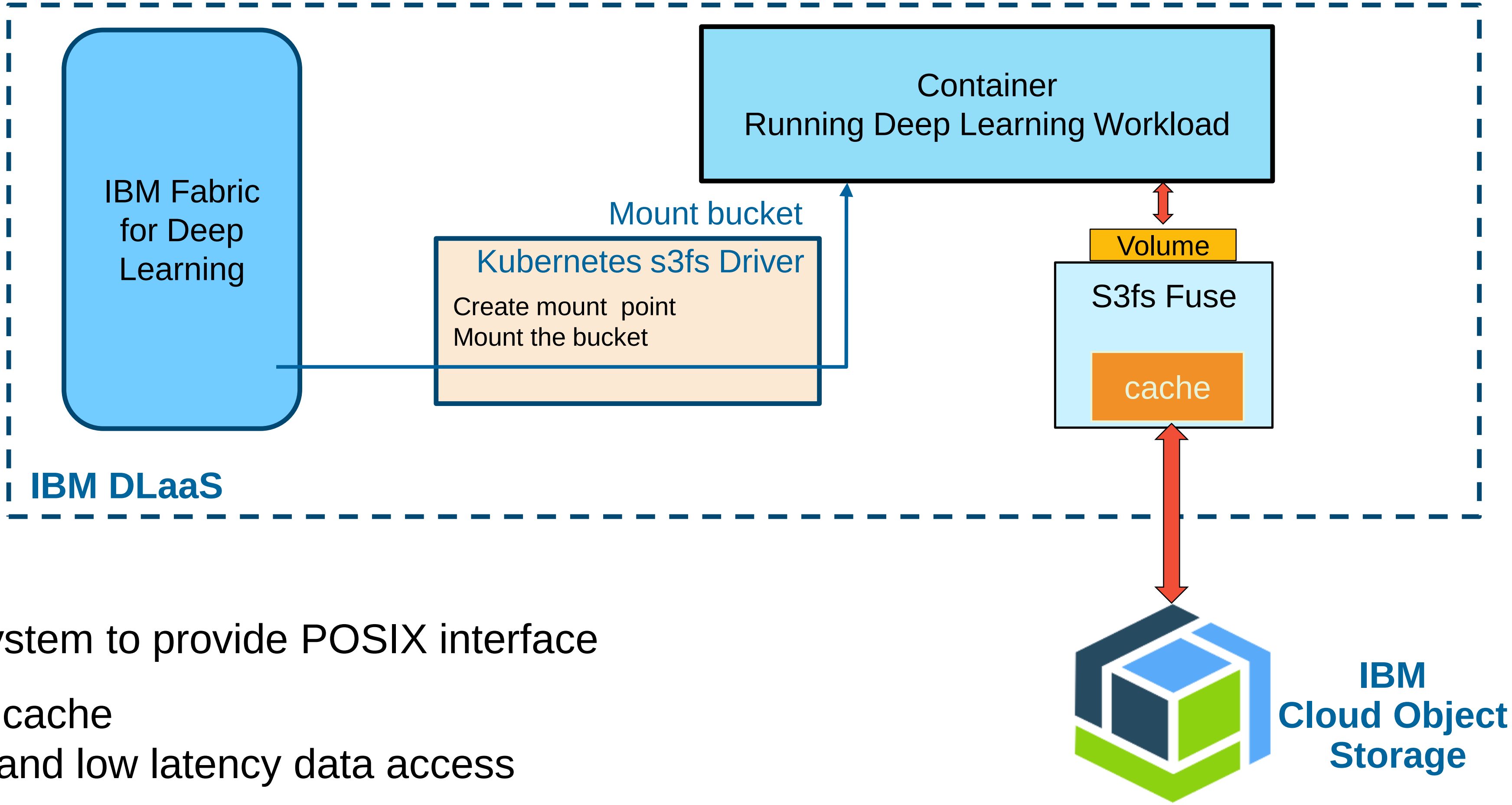


Read ahead prefetching

- Best practices suggest combining multiple training records into a single data file
  - E.g., TFRecord in Tensorflow or HDF5 in pyTorch
  - Makes it easy to mix, match, and shuffle data sets
- Small objects suffer disproportionately from the overhead of the time-to-first-byte from the object storage service
- But when data is packaged into larger objects, the read-ahead feature of the cache avoids this overhead all together

Implementation

- Deployed in IBM Deep Learning as a Service (DLaaS) on the IBM Cloud
- Machine learning workload runs on Kubernetes containers
- Training data and trained model stored in IBM Cloud Object Storage



- Use s3fs FUSE based file system to provide POSIX interface
- Leverage a local in-memory cache
  – provide high throughput and low latency data access
- Supply data faster than object store single connection speeds

Open source contributions

- Kubernetes driver for s3fs available as part of Fabric for Deep Learning
- https://github.com/ibm/ffdl

Fabric for Deep Learning (FfDL)

- S3fs enhancements have been contributed to the s3fs project repository
- https://github.com/s3fs-fuse/s3fs-fuse

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