Running High Performance POSIX Deep Learning Workloads with Object Storage

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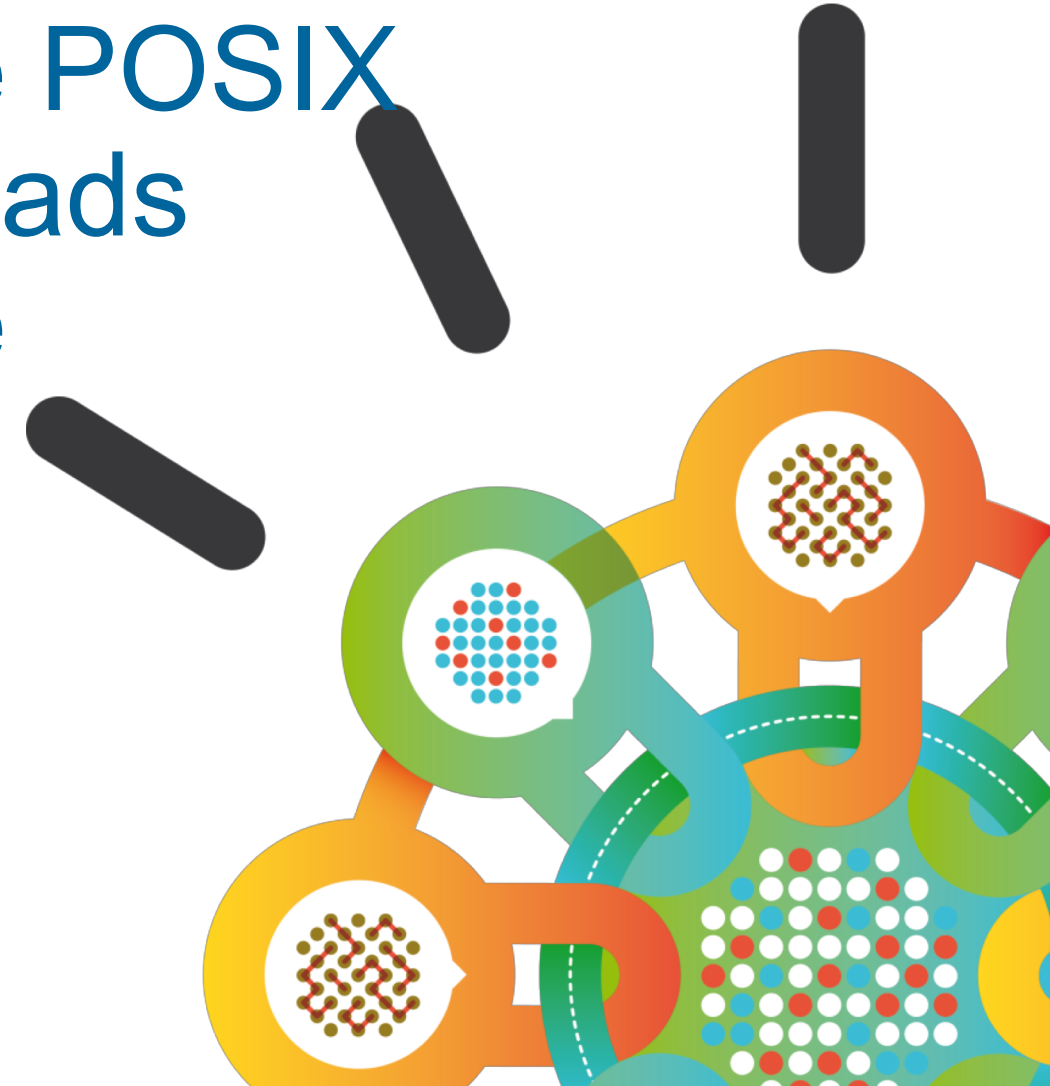

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Background

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

- 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

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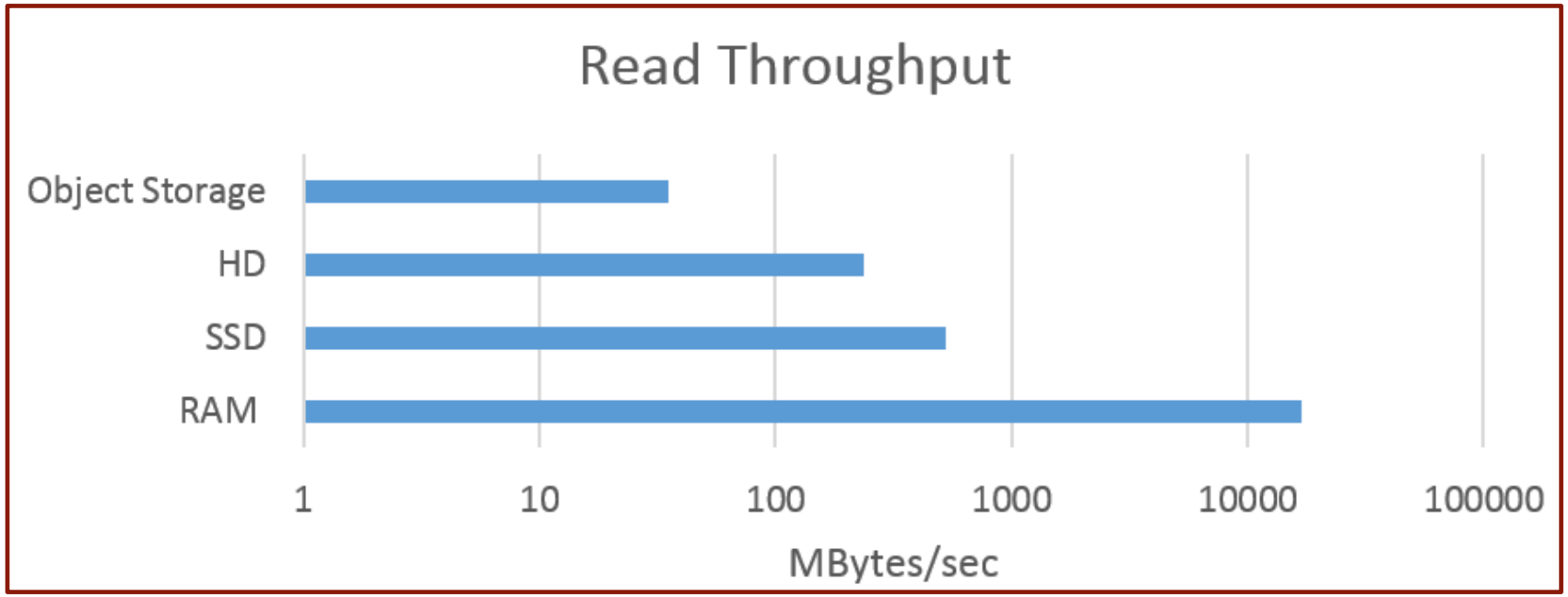
The Challenge

- 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 workloads on data that resides in inexpensive object storage without the need to pre-load or stage the data

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How Much Throughput is Good Enough?

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

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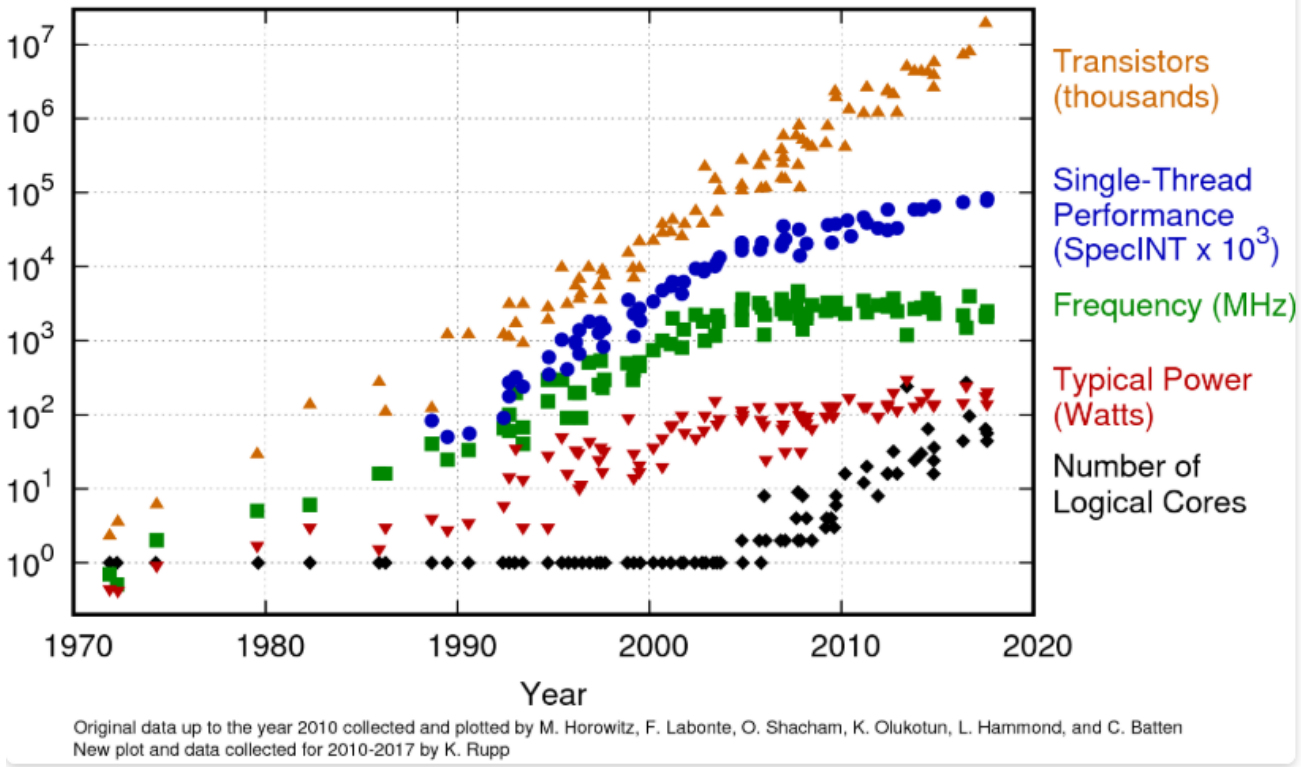
Keeping Up With the GPUs

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

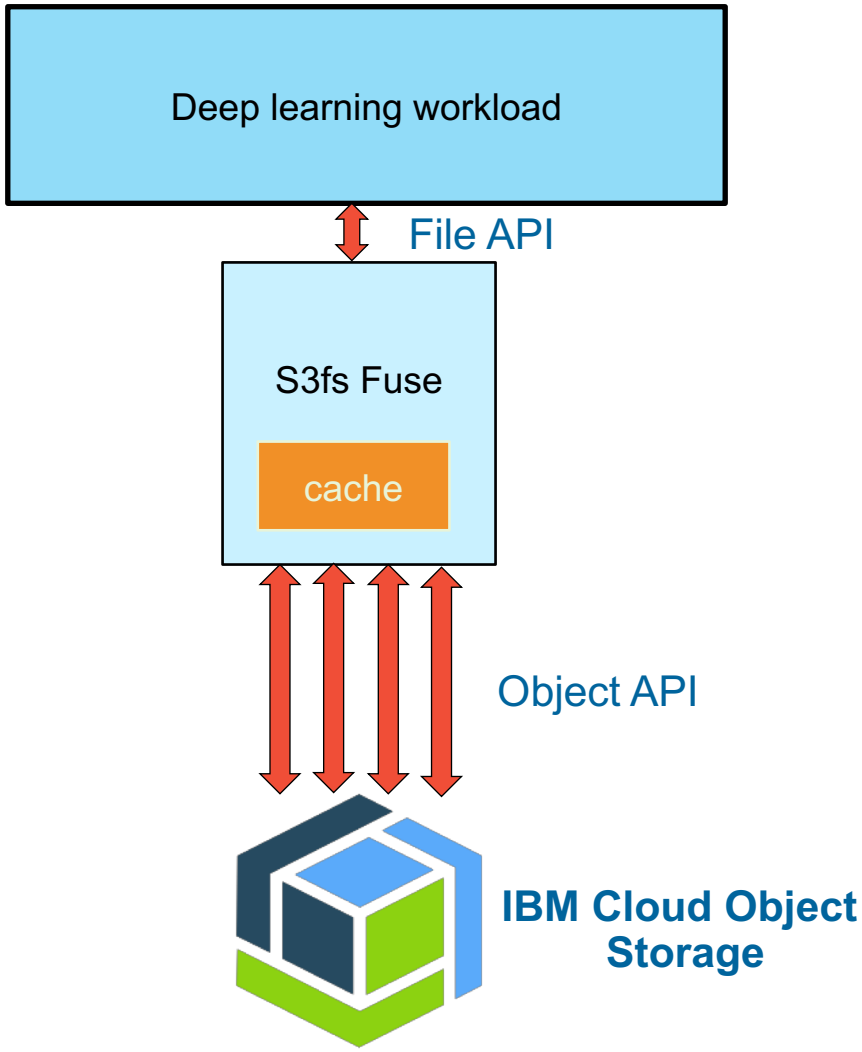
GPUs	Resnet152	Resnet50	VGG11	Alexnet	Speech LSTM
1	28.8	62.9	77.0	246.1	17.8
2	58.3	136.9	122.9	423.9	29.4
4	107.4	224.4	174.4	570.1	64.3
8	180.6	370.6	208.9	526.4	107.0

- 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?



Architecture

- Keep the data on inexpensive object storage
  - Training data
  - Results (logs + trained model)
- Support existing deep learning workloads without modifications
  - Enable deep learning workload to continue using POSIX interface
- Keep the GPUs busy
  - Supply data faster than object store single connection speeds
  - Support prefetching and optimize traffic
  - Leverage a local in-memory cache



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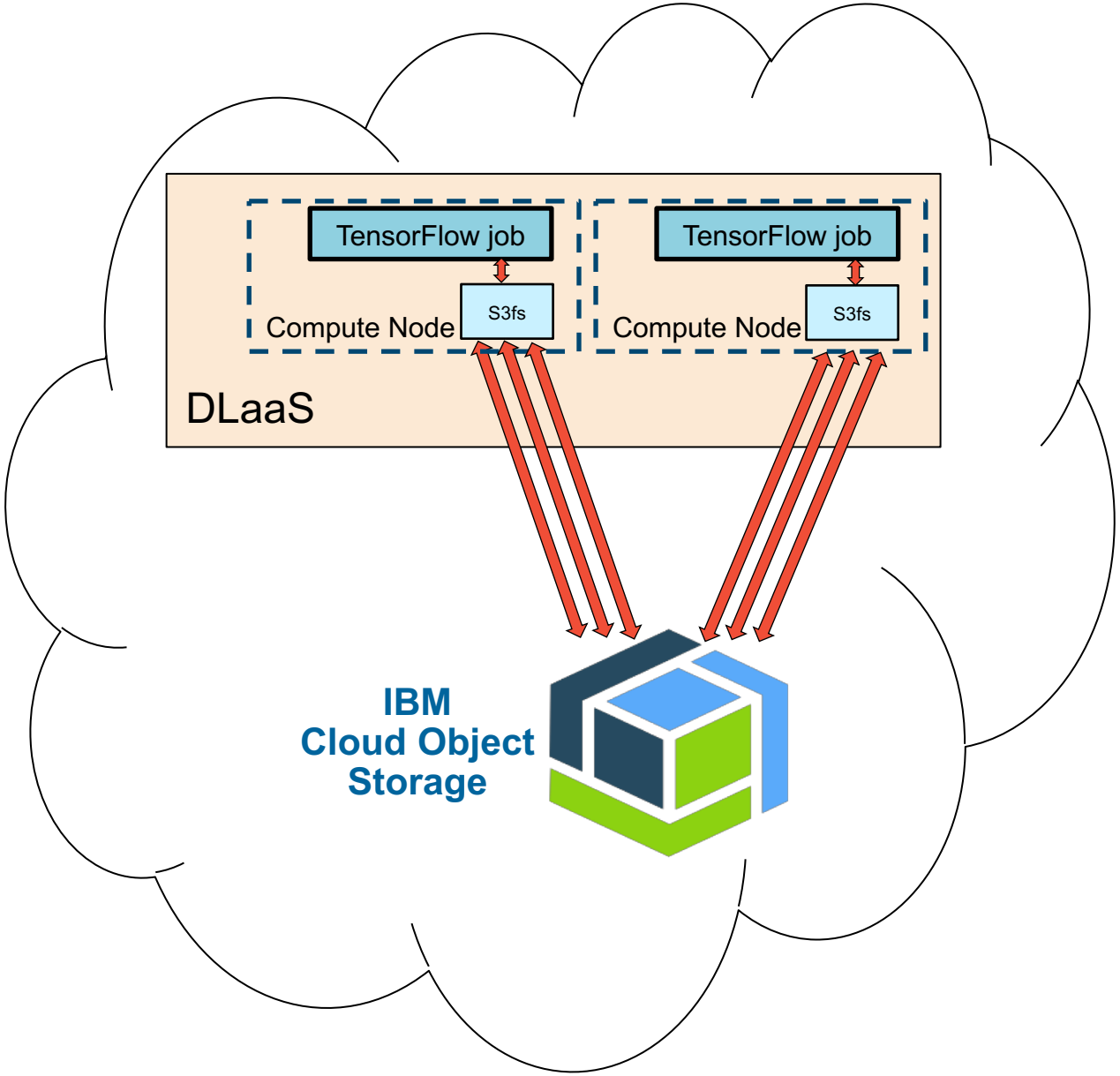
Supply Data Faster Than Object Store Single Connection Speed

- 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



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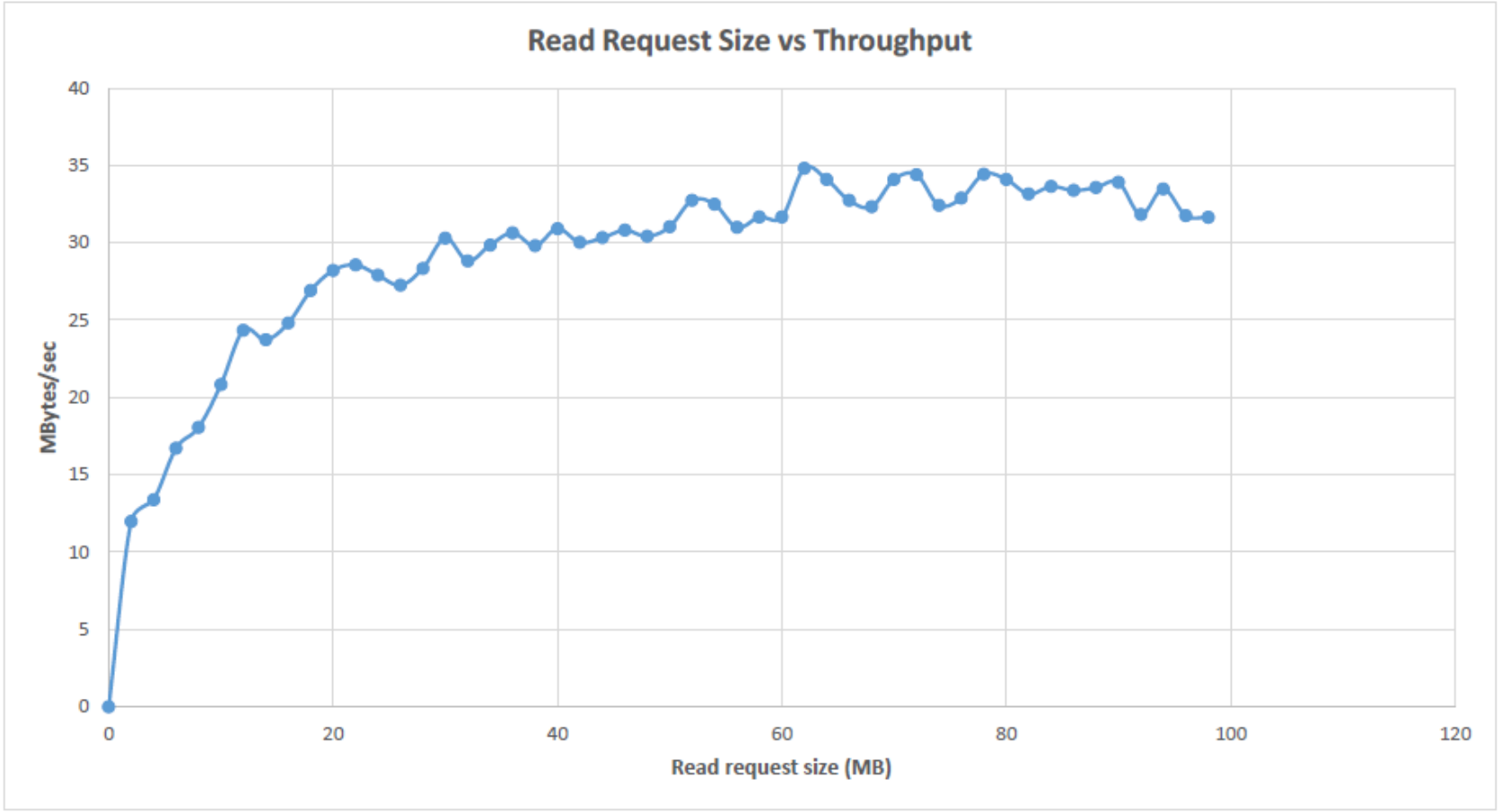
Reading in Chunks

- 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

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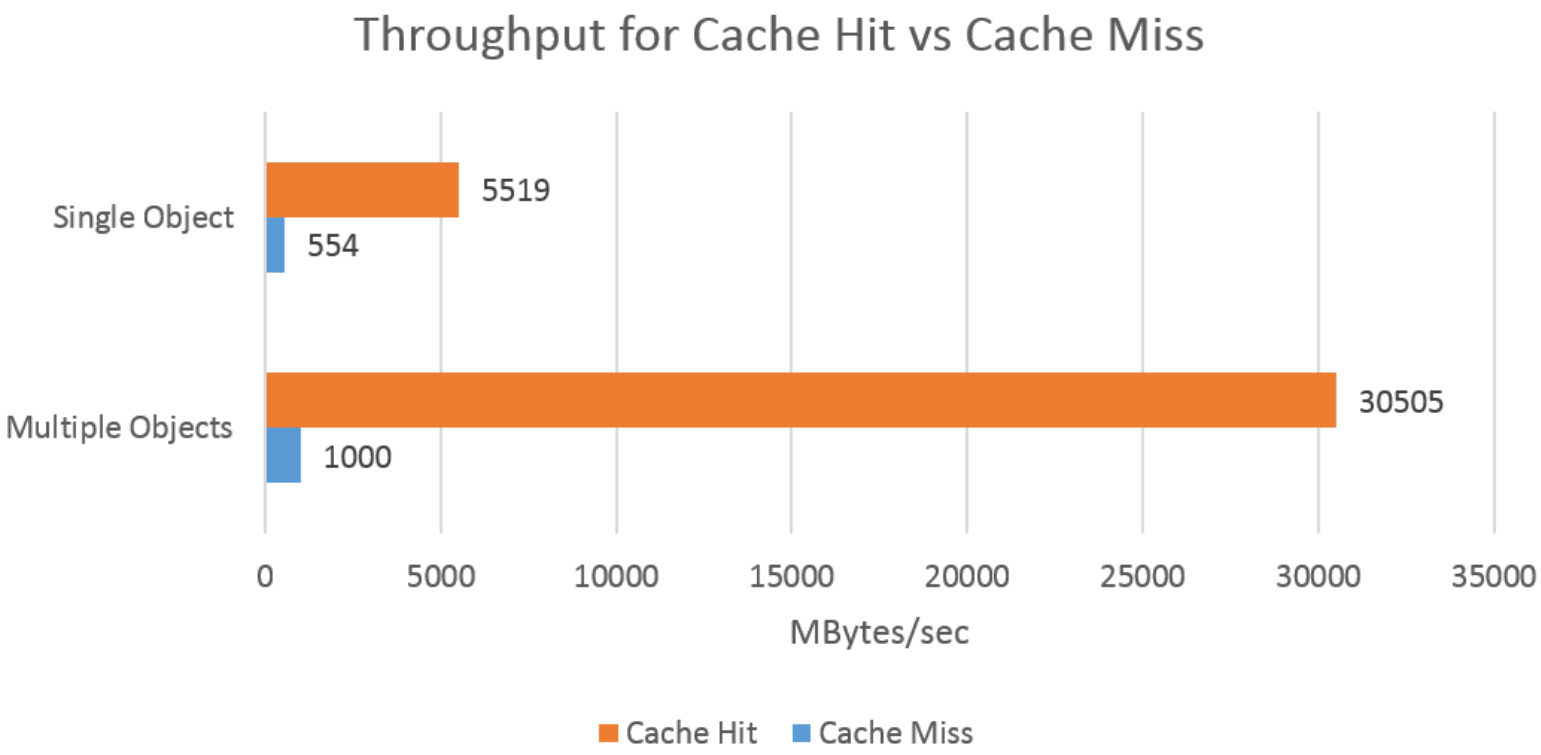
In-Memory Cache

- We have deployed an in-memory cache using the Linux kernel page cache
- Collocated with the compute nodes
- Caching both
  - data chunks
  - meta data
- Limited by
  - client side network bandwidth
  - overheads from the FUSE fs
  - client side copy
- 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



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Small Objects Overhead – Read Ahead Prefetching

- Small objects suffer disproportionately from the overhead of the time-to-first-byte from object storage
- 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
- But when data is packaged into larger objects, the read-ahead feature of the cache avoids this overhead

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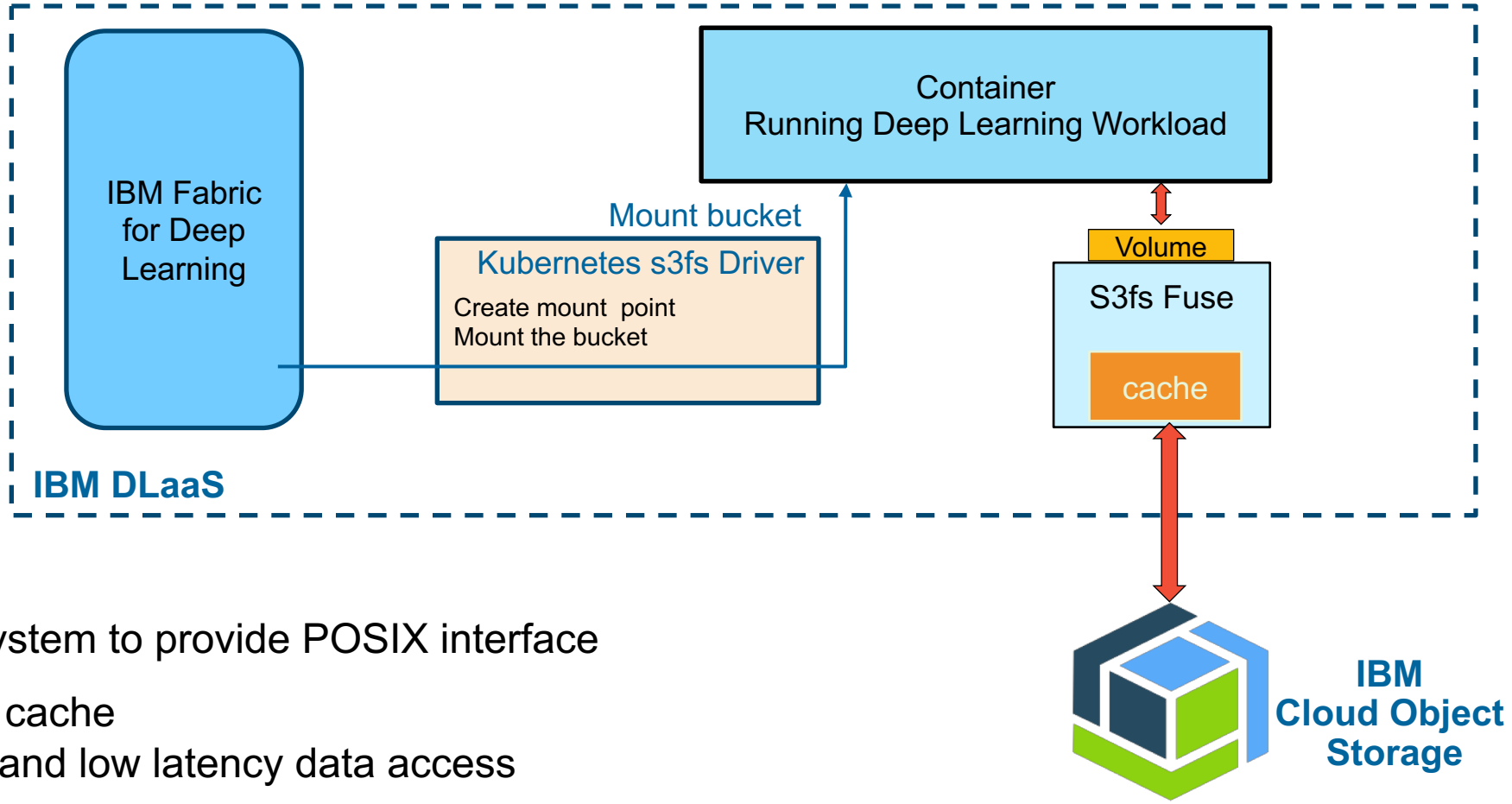
Implementation

- Deployed in IBM Deep Learning as a Service (DLaaS) and IBM Cloud Kubernetes Service (IKS) 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

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Open Source Contributions

- The core of Deep Learning as a Service
  - A deep learning platform offering TensorFlow, Caffe, PyTorch etc. as a Service on Kubernetes

  https://github.com/ibm/ffdl

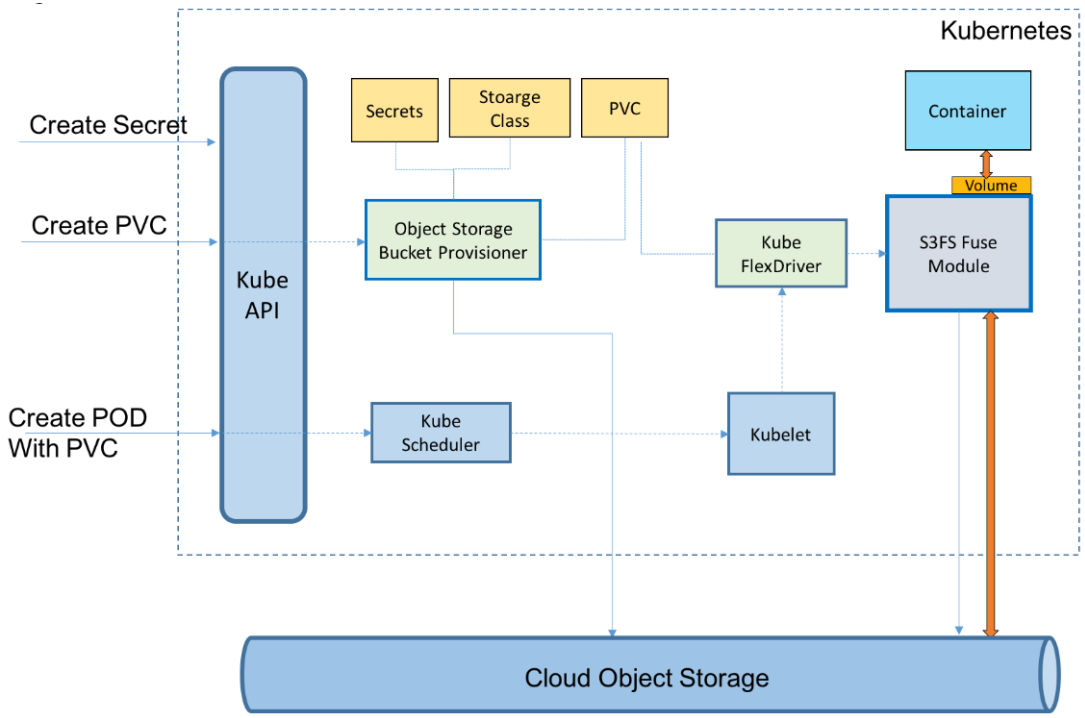
- Kubernetes volume plug-in that enables pods to access IBM Cloud Object Storage buckets. Includes:
  - A dynamic provisioner
  - A driver for mounting the buckets using s3fs-fuse on a worker node

  https://github.com/IBM/ibmcloud-object-storage-plugin

- S3fs enhancements have been contributed to the s3fs project repository

  https://github.com/s3fs-fuse/s3fs-fuse

Fabric for Deep Learning (FfDL)



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