Accelerating Transfer Learning with Near-Data Computation on Cloud Object Stores

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ABSTRACT
Storage disaggregation underlies today’s cloud and is naturally complemented by pushing down some computation to storage, thus mitigating the potential network bottleneck between the storage and compute tiers. We show how ML training benefits from storage pushdowns by focusing on transfer learning (TL), the widespread technique that democratizes ML by reusing existing knowledge on related tasks. We propose HAPI, a new TL processing system centered around two complementary techniques that address challenges introduced by disaggregation. First, applications must carefully balance execution across tiers for performance. HAPI judiciously splits the TL computation during the feature extraction phase yielding pushdowns that not only improve network time but also improve total TL training time by overlapping the execution of consecutive training iterations across tiers. Second, operators want resource efficiency from the storage-side computational resources. HAPI employs storage-side batch size adaptation allowing increased storage-side pushdown concurrency without affecting training accuracy. HAPI yields up to 2.5× training speed-up while choosing in 86.8% of cases the best performing split point or one that is at most 5% off from the best.

1 INTRODUCTION
Storage disaggregation (i.e., the separation of the storage and compute tiers) powers today’s cloud object stores (COS) (e.g., Amazon S3 [2], Google Cloud Storage [27], Azure Blob Storage [11]) as it reduces costs and simplifies management by allowing the two tiers to scale independently. Unfortunately, these benefits come at the cost of a potential network bottleneck [1, 73, 75] between the tiers as network bandwidth growth is outpaced by storage bandwidth and compute throughput growth [23, 70]. Near-data computation techniques are the natural complement to storage disaggregation. These involve provisioning storage-side compute resources to run part of an application (called a pushdown) in order to mitigate the network bottleneck by reducing the amount of data transferred between tiers. These storage-side compute resources are limited by design as they are not meant to replace the compute tier. Following the initial success of pushdowns for a restricted set of workloads (e.g., SQL [7]), there is renewed interest in broadening the applicability of such pushdowns to new applications and to specialized hardware.

This paper shows how ML training can benefit from pushdowns to disaggregated storage by focusing on transfer learning (TL) [80], a widespread ML technique [15] that enables a generic model previously trained (pre-trained) on a large dataset to be efficiently customized (fine-tuned) for a related task. TL democratizes ML by lowering the entry bar, as fine-tuning existing models avoids the need for new, large datasets and the computational expense of training models from scratch. Thus, TL has become a cornerstone of modern cloud ML services [3, 4, 14, 16], enabling the use of pre-trained models and scalable fine-tuning capabilities across major platforms. In traditional TL fine-tuning, the initial DNN layers perform feature extraction while the rest perform re-training.

This paper proposes HAPI¹, a new TL fine-tuning system that spans the storage and compute tiers and judiciously pushes down to storage part of the TL DNN. HAPI leverages two new techniques that address challenges introduced by storage disaggregation for the benefit of both users and operators. The first challenge is that pushdowns make it harder for applications and users to optimize performance. Typically, pushdowns are chosen to minimize network time by having the pushdown’s output be smaller than the job’s input. HAPI builds on the insight that, for reducing TL fine-tuning time, pushing down only to minimize network time is

¹HAPI was the Egyptian god of the annual flooding of the Nile, often portrayed as binding two regions (splits) of Egypt (https://en.wikipedia.org/wiki/Hapi_(Nile_god)).
The insight is that one can use a significantly smaller batch TL DNN naturally decouples the batch sizes used in each tier. The second challenge, particularly important to operators, consists in using the limited storage-side compute resources efficiently. Specifically, the contributions of this paper are:

1. Identifying and demonstrating the benefits of applying near-data computation techniques to TL on top of the disaggregated COS.
2. A measurement study of DNN layer characteristics across 7 popular DNNs (§3), including modern architectures like the Vision Transformer (ViT) and widely-used CNNs such as ResNet and DenseNet. These characteristics play an important role in our system design.
3. Hapì, an end-to-end system comprising two key design techniques: DNN splitting (§4.3) and storage-side batch size adaptation (§4.4) which reduce network transfers, improve training runtime and enable increased pushdown concurrency in the COS.
4. An extensive evaluation (§5) showing up to 2.5× speed-up in training runtime while choosing in 86.8% of cases the best performing split point or one that is at most 5% off from the best.

The paper is organized as follows. We provide background in §2 and present our measurement study in §3. §4 presents the design and implementation of Hapì. We show experimental results in §5 and discuss related work in §6.

2 BACKGROUND

2.1 Transfer learning

TL democratizes ML by allowing knowledge from a model pre-trained on a large dataset to be adapted and reused (fine-tuned) for a different but related task [69]. In doing so, the DNN training time and the generalization error are reduced [26]. As models grow in size and complexity, TL has become increasingly essential for efficiently adapting pre-trained models to specific tasks with fewer resources, making their deployment more practical across various domains. The intuition behind TL is that the pre-trained model, often referred to as a backbone, captures generalizable embeddings (representations of the input data) which can be adapted or fine-tuned for new tasks rather than requiring a model to be trained from scratch. Examples of backbones include convolutional neural networks (CNNs) and Vision Transformers (ViTs) for computer vision [66], as well as models like BERT [20] and GPT [8] for natural language processing (NLP). Recent advances in Vision Transformers [17, 28, 68] exemplify this approach by providing scalable and reusable backbones that can be fine-tuned for a wide range of tasks, including classification, detection, and segmentation.

Figure 1: Overview of TL fine-tuning.

The key to TL lies in fine-tuning the pre-trained model, as depicted in Figure 1. Pre-training is usually done on a different system and often by a different entity and is outside the scope of this paper. Traditionally, fine-tuning is divided further into two phases: (i) feature extraction, where embeddings or high-level representations are extracted from new input data using (partially or entirely) the pre-trained model, and then (ii) training, to create a new classifier using the extracted embeddings [26]. Typically, the early layers of
the pre-trained model, which capture more general features (e.g., edges, textures in vision models), are frozen during fine-tuning, i.e., the model weights of these layers (in red in Figure 1) are not updated with backpropagation. Every iteration (i.e., input batch processed) involves feature extraction followed by training. We refer to the last frozen layer as the freeze layer (or index).

2.2 Cloud object stores
Cloud object stores (COS), such as Amazon S3 [2], Google Cloud Storage [27], and Azure Blob Storage [11], are a popular way to store large-scale unstructured data, providing ease of use, high availability, high scalability, and durability at a low cost [51]. COS are the prime example of storage disaggregation. The COS is connected to the compute tier by a network that, unfortunately, is a bottleneck [23, 46, 47, 60] even when the network is maxed out. The reason are hardware trends. The network bandwidth between the COS and the compute tier is lower than the internal storage bandwidth of COS servers and also lower than the computation throughput [23, 49]. The typical network bandwidth of a single cloud server is 25 - 400 Gbps (3.125 - 50 Gbps) [23, 38, 61, 71]. A single modern NVMe SSD can read sequentially at well over 10 GBps [10, 48], so a couple of NVMe SSDs are sufficient to max out the network bandwidth. In practice, storage servers are provisioned with many SSDs; an array of PCIe 5.0 NVMe SSDs can exceed 100 GBps in read throughput [48]. Other storage media are faster than SSDs, further aggravating the network bottleneck. With sufficient thread parallelism, DRAM reads can exceed 100 GBps, and persistent memory reads can exceed 30 GBps [72]. Compute throughput also exceeds network bandwidth [23, 49]. Earlier studies [46, 60] have reported network read throughput as low as 100 MBps per connection from Amazon S3 but the trend is for network bandwidth to improve. More recently, up to 100 Gbps from general purpose instances to S3 has been reported [21].

In light of this enduring network bottleneck, an important trend has been to push down computation inside the COS, to reduce the amount of data sent over the network. Pushdowns were initially restricted to a subset of SQL (e.g., Amazon S3 Select [7]), but there is a renewed effort in the industry to support more complex pushdowns for computations such as image processing [13] or analytics [1]. There has been growing interest in pushing down parts of ML computations to storage [45, 67]. This trend goes hand-in-hand with another development, enabling pushdowns to use specialized hardware (§2.3).

Despite these trends, two challenges remain for COS users. The network may remain a bottleneck despite the pushdowns, and the COS computational resources are scarce and need to be used efficiently as they are only meant to mitigate the network bottleneck and not replace the compute tier.

2.3 Hardware-accelerated pushdowns
Pushdowns were initially restricted to a subset of SQL, including filtering, projecting, and aggregation (e.g., Amazon S3 Select [7]). The current, natural trend is to offer the benefits of pushing down to a wider range of applications. Unfortunately, restricting pushdowns to CPUs can lead to wasted resources and performance. First, for more complex operations, CPUs can become a bottleneck. Studies show that even with 32 cores, an SGD optimizer can fully utilize the CPU when using a 100 Gbps network [42]. Second, it is not sufficient for the CPU processing to be just faster than the network because the output of a pushdown may be smaller than its input. For example, for a pushdown to generate an output at 100 GBps, assuming an input/output ratio of 2, it needs to process input at 25 GBps. Finally, the aggregate storage bandwidth of a storage server tends to increase faster than CPU capabilities [70].

As a result, the current trend is to allow pushdowns to use specialized hardware such as GPUs. Several works [12, 31] have proposed to use them in storage systems to speed up erasure coding. Finally, there is a push to more-closely integrate storage with GPUs, which further increases the appeal of next-to-storage GPUs. For example, IBM’s Storage Scale System 6000 [39] integrates NVIDIA GPUDirect Storage [57], enabling a direct data path between GPU memory and storage to reduce latency and enhance performance for AI and data-intensive workloads.

3 Measurement Study
Next, we present a detailed measurement study of 7 DNNs. These include a state-of-the-art Vision Transformer [66] as well as several widely-adopted foundational models such as ResNet50 [33], DenseNet121 [36], and VGG19 [64]. These models cover a diverse range of architectural characteristics, making them well-suited for evaluating system-level performance in terms of speed and resource efficiency. We characterize the per-layer properties across three dimensions: output size, compute time, and maximum GPU memory used. These properties all play a role in HAPI’s design (§4). Additional layer-related information for each DNN can be found in Table 2. For the DNNs structured as a sequence of blocks (e.g. ResNets) we count one block as one layer and we use only block boundaries as candidate split points. The input dataset is ImageNet. For readability purposes we group the models into 3 sub-groups in each figure.

Hardware setup. For this section we use two identical GPU-accelerated machines from a public cloud one for the HAPI client and the other for the COS and the HAPI server.
Each machine has an Intel Xeon Gold 6278C CPU with 16 cores, 64 GB RAM, 1 Tesla T4 GPU with 16 GB RAM, a 300 GB SSD and runs Ubuntu 20.04 server 64 bit with CUDA 11.2. The network bandwidth between VMs is 12 Gbps.

**Per-layer output size.** Figure 2a shows the per-layer output size. For reference, the size of a pre-processed ImageNet input tensor is shown with the horizontal dotted blue line. This output size is for a batch size of 1. One can accurately extrapolate from this by multiplying by a specific batch size.

The important observation is that for most models, early on in the DNN structure, there exist layers with a comparatively small output size, often significantly smaller than subsequent layers (e.g. ResNet layer 4, AlexNet layers 3 and 6). These layers are good candidates for splitting the TL application between the COS and the compute tier. Overall, the layer output size generally increases in the beginning (with convolution layers) and then decreases (with pooling layers) but not in a monotonic fashion. While only a few split points have an output size smaller than the pre-processed tensor, we will show that this is not strictly necessary for performance gains because optimizing the network time is only part of the story. Hapi owes its benefits to balancing network time against the computation time in both tiers.

**Per-layer computation time.** Figure 2b shows the per-layer computation time for the forward pass for a batch size of 128. The insights are that some models are more lightweight (e.g. AlexNet) than others and that some models (e.g. DenseNet) show significant variability across layers. However, the forward pass time remains relatively stable with an increase in layer index and gives Hapi the flexibility to balance computation time across the two tiers.

**Per-layer maximum GPU memory usage.** Figure 2c shows the maximum amount of GPU memory needed for the processing of each layer for a batch size of 128. Again, the variation is model dependent and for each model there is variability between layers. Generally, the first few layers use more memory suggesting that these need to be the focal point if reducing memory consumption is desired.

**The need for a dynamic splitting algorithm.** We next motivate Hapi’s dynamic splitting approach by showing the limitations of static splitting approaches.

Figure 3 shows 7 groups of bars. Each group represents a model (listed on the x-axis) and the 7 bars in each group represent different batch sizes (128, 256, 512, 1024, 1536, 2048, 3072 from left to right). The figure summarizes a performance sweep over all possible split points in the DNNs (after each layer). The figure shows per-epoch runtime normalized to splitting at the freezing layer (@Freeze). The points (blue rectangle, red circle) show two other sensible static splits: (1) with red circles @Min, splitting at the layer with the smallest output (earliest such layer as a tiebreaker) and (2) with blue rectangles NoSplit, i.e., sending the entire input to the compute tier. The lines show the speed-up range for all other splits, except the three mentioned above (@Freeze, @Min, NoSplit). If some of the static splits do not appear (e.g. Vgg11, Vgg19, Transformer) it is because they cause OOMs on the client. However, @Freeze (y-axis value = 1) never OOMs.

![Figure 2: A measurement study of 3 per-layer properties for 7 popular DNNs.](image)

Several insights can be derived from the figure, which point to the need for an intelligent dynamic splitting algorithm. First, no static splitting strategy wins in all cases. Second, even though one splitting strategy is the best option...
in some cases (e.g. @Min for ResNet18), it can be very sub-optimal in other cases (e.g. @Min for DenseNet or Vgg19). Third, the behavior is model dependent and the training batch size also matters. Finally, some splits lead to OOMs on the client side and thus should be avoided. This is noticeable in the fact that some splits do not show up in the figure (e.g. NoSplit for larger batch sizes for several models or @Min for Transformer). For the largest 3 batch sizes for Transformer only @Freeze does not result in an OOM which results in no vertical bars (i.e., the speed-up range is 1).

4 DESIGN AND IMPLEMENTATION

4.1 Main insights

HAPI’s two main techniques (1) splitting the TL DNN between the storage and compute tiers and (2) storage-side batch size adaptation are based on the following insights:

(1) Judicious splitting of the DNN’s feature extraction phase between the storage and compute tiers can minimize training time by balancing two factors: the amount of data sent over the network and the overlap in processing time on the storage and compute tiers (§4.3).

(2) Splitting the DNN naturally decouples the batch size of feature extraction from that of training and thus allows HAPI to adapt the former (§4.4). This yields significant reductions in the storage-side GPU memory used, avoiding OOM errors and enabling increased pushdown concurrency in the COS.

(3) Adapting the storage-side feature extraction batch size does not affect training accuracy. By design, HAPI maintains the same training accuracy as if the training was fully performed in the compute tier without push-downs and without batch size adaptation. The reasons are the following. First, HAPI keeps the training batch size and its contents unaffected. Second, feature extraction uses frozen weights (fixed, not re-trained) so its output is deterministic.

4.2 Design overview

At the high level. As shown in Figure 4, HAPI has two components: the HAPI client, which runs on the compute tier, and the HAPI server, which runs in the COS. The client decides at which layer to split the DNN using a runtime estimation model which leverages in-job profiling information. The server executes feature extraction up to the layer decided by the client while employing batch size adaptation. Each storage machine runs one HAPI server.

The communication between the HAPI clients and servers occurs at the granularity of a request. These requests are lightweight and several may be sent by the client to obtain data for a single training iteration especially if the training batch size is large. This is key to leveraging parallelism in the storage tier as one or several HAPI servers can process requests from one iteration in parallel. HAPI servers treat requests independently, in a stateless manner. This combination of lightweight requests and stateless storage-side processing has practical benefits: it simplifies load balancing, failure recovery and scalability as any storage server can handle any request.

On the COS side we differentiate between proxy and storage nodes. The HAPI server runs on the COS proxy. There is a fast network between the COS proxy and the COS storage nodes which host the DNNs and the dataset. However, the network between the compute tier and the COS is more limited in bandwidth.

Terminology. The DNN layer at which HAPI decides to split the DNN is the split index (or layer). The freeze index (or layer) is the DNN layer that separates feature extraction from training, and it is chosen by the user. The training batch size is the batch size specified by the user, and it is used in the training phase. HAPI may decide to use a different batch size for computation on the COS (§4.4); we call this the COS batch size. We use POST request to refer to a request sent from the HAPI client to the HAPI server. We use storage request to refer to a request sent by the HAPI server to the storage nodes.

Request flow. To initiate a TL computation, users provide their application to the HAPI client, which extracts the application configuration (e.g., the model type, the dataset, the freeze index) and, after some profiling, splits (§4.3) the DNN into 2 parts: one to be executed on the COS and the other to be executed on the compute tier. Figure 5 depicts an example request flow between the two tiers during one iteration, with a training batch size of 3000 and a split index of 10. The values in Figure 5 are for illustration only.

For each training iteration, the HAPI client sends to the HAPI server HTTP POST requests containing the necessary information: split index, model type, and the name of the
object that stores the corresponding data batch. Several such POST requests may be sent during one iteration to benefit from parallelism on the storage side. In Figure 5, the client sends 3 requests to the storage, each for 1000 objects. Together, these responses for these 3 requests will provide all data for the training batch size of 3000.

When the HAPI server receives a request, it first reads in the training data and the model by sending a storage request to the COS storage nodes and then executes the feature extraction part up to the split index. As an optimization, the server may reuse a model if it already exists in its GPU memory (e.g., from previous requests in the same training job) because weights are frozen on the storage side so requests do not modify the model. Thus, such model reuse does not go against the stateless nature of HAPI’s COS processing.

The HAPI server chooses at will the COS batch size to be used for feature extraction (§4.4). In Figure 5, the server uses a COS batch size of 200 for each request which allows it to execute all 3 requests in parallel without encountering OOMs. That is, the server further divides a request’s work for 1000 objects into 5 sequential partitions of 200 to reduce the memory requirements.

After finishing the feature extraction portion assigned to it, the HAPI server sends back the outputs of the split index to the HAPI client. The client combines the outputs for all requests sent during that iteration and continues the TL computation on the compute tier. Note that the client uses the training batch size for its entire computation even while executing the last part of feature extraction (if any).

**Observations.** First, HAPI only executes feature extraction next to storage in the COS. Consequently, this means that the split index will always be smaller than or equal to the freeze index (i.e., the split is always before the training phase).

Second, as it is typical in current ML frameworks, HAPI pipelines both communication and computation on the client side. That is, requests for iteration $N + 1$ are already sent to the storage just before the client starts its processing for iteration $N$.

Third, scaling down the COS batch size does not affect the convergence and accuracy of TL. This is because the COS batch size is used solely for feature extraction rather than for the actual training.

Fourth, for the requests belonging to one iteration, it is possible for the client to receive results out of order (i.e., the first request sent may not complete first) as the request completion time depends on the COS. To address this, the HAPI client re-orders the intermediate results returned from the server to ensure that the order of data in a training batch does not change, thus maintaining the learning trajectory.

### 4.3 Splitting TL between storage and compute tiers

Splitting the TL computation between the storage and compute tiers is the cornerstone of HAPI’s design. It enables training runtime improvements by navigating the interplay between the amount of data sent over the network and the overlap in processing time between the client and storage sides. Furthermore, it decouples the batch sizes used on the client and storage sides, paving the way for benefits via storage-side batch size adaptation (§4.4).

HAPI’s approach to splitting leverages several components which are detailed in this subsection: (1) a fine-grained profiler, (2) a model that uses the profiler, (3) a GPU memory usage estimator and most importantly (4) a splitting algorithm which uses all other components. HAPI’s contributions are (1), (2) and (4) while for (3) it leverages existing techniques.

**The splitting algorithm.** The goal of the splitting algorithm is to minimize the training runtime for a job by choosing the proper splitting point.

Central to HAPI’s splitting algorithm is the concept of overlap between the processing on the client and storage sides and its interplay with the chosen split point. This is illustrated in Figure 6. During training, HAPI overlaps the storage-side processing for iteration $N + 1$ with the client side processing for iteration $N$. The dominating side ends up dictating the training runtime. By adjusting the split index, HAPI can adjust the amount of overlap and thus directly influence the training runtime. One can think of the overlap as saved runtime because both the storage and client tiers make progress concurrently instead of sequentially. Thus, intuitively, the right strategy is to maximize the overlap. Overall, HAPI balances both network and computation time in the decision process which is essential in minimizing training runtime.
When choosing the split point, accounting only for network time or also accounting for computation time but without accounting for the overlap are both sub-optimal. For example, the motivation section (§3) showed that splitting at the layer with the smallest output is far from optimal. Intuitively, minimizing the network cost alone is insufficient because this is often achieved at a split point that pushes too much work on the storage side, reducing the overlap with the client side. One can also consider both network and computation times but not the overlap by minimizing the sum of the client time, server time and network time. This is a sensible approach inspired by ML inference [43] where for any single inference request there are no iterations and thus no overlap. In our evaluation (§5) we show that this solution also under-performs. The larger the overlap, the more this solution will over-estimate training runtime resulting in sub-optimal split choices.

Algorithm 1 Choose the split index - runs on client

\begin{verbatim}
1: if Right before 1st iteration of epoch 0 then
2:   split_idx = freeze_idx
3: else if job failed with OOM then
4:   return error to client
5: end if

6: if Right before mid iteration of epoch 0 then
7:   split_idx = earliest split not predicted to cause OOM on client
8: end if

9: if At end of epoch 0 then
10:  runtimes={} 
11:  for potential_split in [0, freeze_idx] do
12:     if potential_split predicted to NOT cause OOM on client then
13:       derive RT_SRV at potential_split from profiling & modeling
14:       derive RT_CLI at potential_split from profiling & modeling
15:       derive RT_NW at potential_split from profiling & modeling
16:       NR_IT = nr iterations in an epoch
17:       runtimes[potential_split] =
18:         RT_SRV + max(RT_SRV + RT_NW , RT_CLI) * (NR_IT - 1)
19:   + RT_CLI
20: end if
21: end for
22: split_idx = idx such that runtimes[idx] is minimized
\end{verbatim}

Algorithm 1 presents the steps involved in choosing the split index. This algorithm runs on the client. By default, HAPI uses the first epoch for profiling on both the server and client sides and then uses that information to select a split index for the rest of the epochs. While not default in HAPI, if desired, another epoch can be easily turned into a profiling epoch later on. Usually many epochs are needed for convergence so using one for profiling has negligible impact. Given a stable configuration (i.e., the same split), the behavior of ML training is deterministic across iterations and this ensures the relevance of the profiling.

For the first half of epoch 0 (Alg1:1-5), HAPI uses the freeze index as a split point. This is the minimum amount of work that can be done on the client. If this causes an OOM on the client, then the client is notified because any other split will also OOM. For the second half of epoch 0 (Alg1:6-8), the split index is changed to the earliest split that HAPI predicts will not cause an OOM on the client. Thus, this is the maximum amount of work that the client can perform. This earliest split could be 0 which means that there is actually no splitting (i.e. the input data is sent to the client which does the entire processing). At the end of epoch 0 (Alg1:9-19), HAPI selects the split for subsequent epochs. For each split that will not cause an OOM on the client, the algorithm estimates, using profiling and modeling information, the computation time on the server and client as well as the network time. Using these, it then estimates the per-epoch runtime while accounting for the overlap (Alg1:18). In particular, HAPI considers the overlap between (1) the client side and (2) the server side + network time because the client cannot start processing until it finishes receiving the data from the server.

A few more notes about the splitting algorithm. First, the algorithm is not concerned with the memory usage and OOM on the server side because it does not have access to that information. This is taken care of on the server side by HAPI’s batch size adaptation algorithm. Second, the algorithm may end up choosing to not split at all (split index 0) if it infers that to be the best solution. To estimate epoch runtime with split index 0, HAPI uses a simpler procedure than in Algorithm 1. If split 0 is chosen as the final split, then it means it was already chosen as the earliest split for profiling in the second part of epoch 0 and thus per-iteration runtime is already available. Third, profiling using both the earliest and latest possible splits is particularly important for the case when the client and server have different GPU models with different performance. With a single split, profiling information from the server would have to be used for making estimates on the client side and vice-versa. This can be error prone with heterogeneous GPUs and is avoided with HAPI’s profiling method.

**Profiling and modeling runtime.** To derive epoch runtimes, as described above, we first break down the execution time on both client and server into fine-grained execution
phases and estimate per-phase runtime using a combination of profiling and modeling.

Several of the phase costs are proportional to the split layer’s output size so they are amenable to modeling. To obtain per-layer output sizes, there is a short profiling phase on the client (not included in Algorithm 1), before the job starts, in which the client runs a forward pass over the DNN with a batch size of 1 with a synthetic input. From this, the layer output size for any potential split and batch size can be simply derived.

| Profiling side | Phase description | How to estimate |
|----------------|-------------------|-----------------|
| @server        | read data from storage | profiled       |
| @server        | read model to GPU | profiled       |
| @server        | move data to GPU | profiled       |
| @server        | forward pass | linear w.r.t data size |
| @server        | move data out of GPU | linear w.r.t data size |
| @server        | pickle for network transfer | linear w.r.t data size |
| @client        | network bandwidth | profiled       |
| @client        | unpickle received data | linear w.r.t data size |
| @client        | create dataloader | linear w.r.t data size |
| @client        | copy data to GPU | linear w.r.t data size |
| @client        | forward pass | profiled       |
| @client        | backward pass | profiled       |

Table 1: Profiled execution phases including the location where the profiling takes place.

Table 1 shows the phases that we profile or model. The modeled phases have a cost that is proportional to the output size. The cost can be derived with knowledge of the layer output sizes and characteristics of the environment (e.g. memory bandwidth, pickle throughput). The environment characteristics are learned once per machine type and are job-agnostic.

The final step is to estimate the entire server-side and client-side processing times ($RT_{SRV}$ and $RT_{CLI}$ in Algorithm 1) using per-phase estimates. The main challenge lies on the server-side in accounting for the impact of concurrency and waiting time. For concurrency, we model the GPU-only forward pass as sequential execution as our GPU (Nvidia T4) is time-shared. We consider all other costs perfectly parallelizable. Request waiting time can become a factor when some requests are queued at a storage server waiting for other requests to finish. For the case of concurrency among requests from the same training job, we modeled waiting time as the execution time of the wave of requests in front. To explain, consider 8 requests sent to a storage server of which 4 can be executed in parallel. The waiting time for the last 4 requests is the execution time of the first 4 requests. For the general cases of different concurrent jobs, the HAPI server would have to expose the expected waiting time to the HAPI client.

Memory usage estimation A memory estimator is needed for Algorithm 1. There is already past work on this topic [24] and HAPI does not make a contribution in this respect. We use a simple estimation approach based on the intuition that the maximum amount of memory for the forward pass occurs at the layer which has the largest input + output size. We obtain these sizes as described above. We couple this approach with a past understanding of the jobs we run.

We note the following insights. Under-estimating memory for a specific split can cause client-side OOMs. Over-estimating memory usage can cause, in some cases, skipping optimal split points. This can occur, for example, when the estimate points to a client-side OOM for the optimal split while in reality there is no OOM. Thus, over-estimation is preferable to under-estimation.

4.4 Storage-side batch size adaptation

Batch size adaptation in this paper refers to HAPI reducing the COS batch size on the server side. As discussed, this is enabled by splitting which decouples the client and COS batch sizes, thereby allowing both to be chosen independently. As previously mentioned, batch size adaptation does not affect the final training accuracy. This is because batch size adaptation only applies to the feature extraction phase.

Memory saving. The main benefit of batch size adaptation comes from dramatically reducing the amount of GPU memory needed on the storage-side. A positive effect of that reduction is that this frees sufficient GPU memory to allow increased server-side request parallelism.

Without batch size adaptation, the GPU memory needed is a function of the training batch size and layer output sizes. If the user employs large training batch sizes then this runs the risk of OOMs. With batch size adaptation, the storage-side GPU memory needed is a function of the COS batch size and layer output sizes. There are two reasons why this results in significant server-side GPU memory savings. First, the COS batch size can be orders of magnitude smaller than the training batch size. Second, as shown in §3, the layers with the largest output sizes (and which can consequently yield the largest memory savings) appear in the first part of the DNN which is exactly the part that is pushed down to storage and benefits from batch size adaptation.

Note that HAPI’s design based on requests is already a manifestation of batch size adaptation since the training batch on the client side is reconstructed from several smaller
requests sent to the storage. HAPI applies batch size adaptation further inside a single request by reducing the COS batch size.

Choosing a COS batch size. We found that using a static COS batch size across all workloads is sufficient because we found no relationship between COS batch size and a request’s processing time on the storage side. We found no benefits from increasing the COS batch size beyond a certain value. The main thing to avoid is choosing a value that is too low which results in unnecessary overhead. HAPI uses a storage batch size of 16 objects.

An added benefit of this approach is that the batch size assignment is quick. More complicated approaches may delay the completion time especially for particularly lightweight requests. Indeed, we saw this initially when we experimented with a dynamic programming approach that chose a potentially different COS batch size for every request already queued at the server.

4.5 System implementation
We use PyTorch [58] for ML computation on both the client and server sides.

The HAPI server. We integrated HAPI’s server in the COS proxy server by incorporating the batch size adaptation algorithm and additional functions for ML computation. When the server receives a POST request, it reads the object holding the training data from storage and passes it to the ML function for processing. Each incoming request is served by a separate OS process. On the ML side, we created custom DNN models that are capable of running the forward pass between arbitrary start and end layers. This enables us to split the computation at any chosen layer.

The HAPI client. Apart from choosing the split index for the model, the HAPI client is responsible for running the user’s TL code. To integrate with our system, two modifications were necessary in the vanilla training code. First, we use our custom models to enable starting computation from an arbitrary layer instead of being restricted to the default first layer. Second, instead of streaming the raw training data using HTTP GET requests, we stream the intermediate outputs (resulting from the last layer executed on the COS) using HTTP POST requests. Moreover, users provide the same training parameters in both cases, whether using the status quo or HAPI, and hence, the whole process is transparent to them.

5 EVALUATION
5.1 Methodology
Applications. HAPI is application-agnostic: its benefits are orthogonal to the training objective, i.e., any TL application that trains a DNN can use HAPI. It can be used for speech recognition [22, 32] or language modeling [9]. In our evaluation, we focus on image classification as our TL application for two reasons: (1) due to its wide use in both academia and industry, and (2) since the data points (i.e., images) used for such applications are large compared to those of other applications (e.g., text or audio files) and thus create a more challenging environment in terms of communication or computation bottlenecks.

We evaluate a Vision Transformer [66] model along with popular, foundational DNNs from computer vision (ResNets, Vggs, etc). Table 2 lists all models and their freeze layers. The Transformer is a Vision Transformer from the PyTorch TorchVision library. Although originally designed for language modelling tasks, the Transformer has seen extensive applications beyond NLP to image classification [44], video understanding [6], and biological sequence analysis [55]. For the DNNs structured as a sequence of blocks (e.g., ResNets) we count one block as one layer and we split only at block boundaries. The mix of models from Table 2 allows us to cover a wide range of situations (compute intensiveness, output size variation, model size) that influence HAPI’s behavior.

| MODEL   | Alex Net | Res Net18 | Res Net50 | Dense Net | Vgg 11 | Vgg 19 | Transformer |
|---------|----------|-----------|-----------|-----------|--------|--------|-------------|
| Freeze  | 17       | 11        | 21        | 20        | 25     | 36     | 17          |
| Total   | 22       | 14        | 22        | 22        | 28     | 45     | 21          |

Table 2: The 7 models used along with the index of the freezing layer and the total number of layers.

Metrics. As the main metric we use the time to finish one epoch of training. We present this either as relative speed-up when comparing two systems (e.g., by normalizing the runtime of a system to that of a competitor) or as absolute values. We use the runtime of epoch 1 as it is representative of all the epochs that follow. We do not show the training accuracy because, as discussed, HAPI keeps it unchanged by design.

Training input. We use the ImageNet [18] dataset. As the actual input to the DNN we feed tensors resulting from separately pre-processing the input image. This is in line with current approaches to decouple input pre-processing from training [79] in order to not bottleneck the training. The input tensors are already stored on the proxy nodes in CPU DRAM. This allows us to focus on the communication between the client and the server. The tensor size is 224 x 224, the standard input size for vision tasks. We reuse the first 30720 ImageNet images for each training epoch as the pre-processed tensor is always the same size regardless of
the input image. Nevertheless, HAPI can also take images as input and perform pre-processing right before training.

The POST request size is set to 128 objects. We use 7 training batch sizes (BS for brevity) that are multiples of the request size, ranging from small to very large: 128, 256, 512, 1024, 1536, 2048, 3072. Thus, the number of parallel requests sent by the HAPI client to the COS during one iteration equals BS divided by 128.

Batch size adaptation is by default applied to all requests on the server side and we set the default COS batch size to 16. The server sends the data to the client only after finishing the processing for all 128 objects in a request. On the server side, a maximum of 4 requests can be executed concurrently.

By default, HAPI does not reuse the DNN stored in GPU RAM between requests so it re-loads it into the GPU RAM for every new request. We evaluate the benefits of model reuse in §5.6.

**HAPI configuration.** We use cloud VMs, one for the storage and one for the compute tier. Each VM has 64 GB RAM, 16 Xeon Gold 6278C vCPUs and one 16 GB Nvidia T4 GPU and runs Ubuntu 20.04 server 64 bit with CUDA 11.2. The network bandwidth between VMs is 12 Gbps. This is larger than the reported network bandwidth between client tiers and object stores in the past [46, 60] and reflects the current trend towards increased network bandwidth in data centers [21]. Nevertheless, we analyze the sensitivity to network bandwidth in §5.7.

**Competitors.** We compare against 4 competitors (NoSplit, @Freeze, @Min, NSG). The first 3 use either no splitting or where the splitting occurs is equivalent to inference (i.e., no backpropagation / only forward pass).

NoSplit trains solely on the compute tier, streaming as many objects as the training batch size from the COS. @Freeze always splits at the freezing layer. @Min always splits at the layer with the smallest output (as a tiebreaker the earliest such layer is used) up to and including the freezing layer.

The fourth competitor, which we call NSG, is a dynamic approach based on Neurosurgeon [43]. NSG uses the same estimates as HAPI but uses its own splitting algorithm originally designed for inference. That is, it chooses as a split index the one that minimizes the sum of the server-side, client-side and network times. We believe that NSG’s splitting algorithm is also a natural approach for TL training because the part of TL before the freeze point (which is also where the splitting occurs) is equivalent to inference (i.e., no backpropagation / only forward pass).

We purposely equip @Freeze, @Min and NSG with HAPI’s batch size adaptation to avoid storage-side OOMs. While batch size adaptation is the contribution of HAPI, lending it to the competitors allows us to analyze the effectiveness of the different approaches to splitting across a wider range of experiments without being impacted by storage-side OOM. NoSplit does not use batch size adaptation as it does not push down.

**Presentation.** Most plots show results for all 7 models and 7 batch sizes using bar charts which contain 7 groups of bars (one group per model) each with 7 bars (one bar for each batch size). For brevity, we use BS to refer to specific batch size values.

**Summary of the findings:**

1. HAPI improves training runtime compared to all competitors and across all batch sizes (§5.2, §5.3, §5.4).
2. HAPI avoids OOM errors by pushing work to the COS and using batch size adaptation there (§5.2).
3. HAPI chooses split points that are close to the optimal points, much more so than the competitors (§5.5).
4. HAPI’s benefits remain across a range of network bandwidths between client and storage (§5.7).

**5.2 HAPI vs not splitting (NoSplit)**

![Figure 7: Speed-up of HAPI vs NoSplit. The interrupted bars signify infinite speed-up due to OOM in NoSplit.](image-url)

Figure 7 compares the speed-up of HAPI vs NoSplit across all 7 models and 7 batch sizes. The numbers are averaged over 4 runs for each system. Variability is low, the range for both systems is maximum 1.13 and the coefficient of variation is maximum 0.05. The interrupted bars mean infinite speed-up. That occurs when NoSplit fails with client-side OOM while HAPI successfully completes.

HAPI is always equal or better and the speed-up (when not infinite) is as high as 2.5x. In some cases, HAPI and NoSplit are equal (i.e. AlexNet BS 128, Vgg11 BS 128 - 512, Vgg19 BS 128 - 256). This happens when HAPI realizes that the best approach for that configuration is to not split and thus falls back to behaving like NoSplit. Unfortunately, NoSplit OOMs for larger batch sizes for 6 out of the 7 models while HAPI avoids the OOM. Thus, HAPI enables practitioners, if they wish, to use batch sizes beyond the reach of systems that do not split the DNN.
5.3 HAPI vs static splitting (@Freeze,@Min)

The key insight is that whenever the optimal split occurs far from the freezing layer, NSG's splitting approach can become infeasible in order to avoid OOMs on the client side. However, there are differences and NSG improves on @Freeze and @Min (see Vgg19). As before, some of the benefits of HAPI come from its ability to fall back to NoSplit in certain situations but even discarding those cases the speed-up can approach or exceed 1.5x (e.g. Transformer, DenseNet).

**Figure 8:** Speed-up of HAPI over @Freeze. @Freeze always uses the freezing layer as a split point.

**Figure 9:** Speed-up of HAPI over @Min. The interrupted bars signify infinite speed-up due to OOM in @Min. @Min always splits at the layer with the smallest output.

The speed-up for AlexNet, ResNet18 and ResNet50 is generally small because the optimal split point is either close to or equal to the freeze layer or because several of the best split points yield similar runtimes. However, HAPI shows speed-up for AlexNet BS 128 because it falls back to NoSplit while the competitors cannot as they are not dynamic. For the rest of the models the speed-up is larger because the best split points, often chosen by HAPI, are in the middle of the DNN far from the freezing layer. As in §5.2, for small batch sizes for Vgg11 and Vgg19, HAPI also falls back to NoSplit while the competitors cannot. Even discarding the cases where HAPI falls back to NoSplit, the speed-up is larger than 1.5x for several models. The speed-up generally decreases for larger batch sizes because the optimal split point approaches the freeze index for these configurations. The reason is that as the batch size increases, more and more early splits points become infeasible in order to avoid OOMs on the client side.

5.4 HAPI vs dynamic splitting (NSG)

Figure 10 shows the speed-up of HAPI compared to NSG averaged over at least 4 runs each. NSG behaves similarly to @Freeze and @Min because it tends to select splits that come late in the DNN. However, there are differences and NSG improves on @Freeze and @Min (see Vgg19). As before, some of the benefits of HAPI come from its ability to fall back to NoSplit in certain situations but even discarding those cases the speed-up can approach or exceed 1.5x (e.g. Transformer, DenseNet).

**Figure 10:** Speed-up of HAPI over NSG.

**Figure 11:** (Top) Accuracy of per-epoch runtime estimates for HAPI and NSG correlated with (Bottom) the distance from the optimal split (dots) to the freeze layer (vertical bar).

Figure 11 illustrates the limitation of NSG's splitting approach. The top part shows the estimation accuracy for HAPI and for NSG. Note that this accuracy is not training accuracy (that remains unchanged in HAPI) but rather per-epoch runtime estimation accuracy which is an important factor in deciding the splitting point. The bottom part of Figure 11 shows the optimal split point (with bars) and the freeze point (with dots).

The key insight is that whenever the optimal split occurs significantly before the freezing point (the top of the bar is far from the dots in the bottom part of Figure 11), NSG's
estimates are inaccurate because the overlap between the client and server sides is large and NSG does not account for that overlap. As soon as the optimal split is close to the freezing layer (top of the bar is close to the dots) then NSG’s estimates are more accurate. Since NSG does not fall back to NoSplit, the bottom part of Figure 11 only considers the split points greater than 0.

5.5 Optimality of chosen splits
Table 3 shows how close to the optimal are the splits chosen by each system across all models and batch sizes. The sub-optimal splits are binned according to how close the resulting runtime is relative to the runtime for the optimal split. There are 4 bins in increments of 5%. For example, the bin entitled "(10-15)% off" means that the sub-optimal split chosen yielded a runtime between 10% and 15% slower than the optimal split. To obtain the optimal splits we performed a sweep across all split points for each model and batch size.

| %/MODEL | HAPI | NSG | @Freeze | @Min | NoSplit |
|---------|------|-----|---------|------|---------|
| OPTIMAL | 59.2 | 14.8| 8.2 | 4.1 | 12.2 |
| (0-5)% off | 27.6 | 29.3| 26.5 | 28.6 | 0 |
| (5-10)% off | 9.2 | 8.5 | 12.2 | 8.2 | 0 |
| (10-15)% off | 2 | 6.4 | 4.1 | 6.1 | 0 |
| >15% off | 2 | 41 | 49 | 40.8 | 34.7 |
| OOM | 0 | 0 | 0 | 12.2 | 53.1 |

Table 3: Optimality of chosen splits for HAPI compared to the four competitors.

HAPI chooses far more optimal splits than the second best system (59% compared to 14.8% for NSG). If we consider splits off by at most 5% from optimal then HAPI is at 86.8% while NSG reaches 44.1%. HAPI is not perfect. The main reason for the inaccuracies (especially for the bucket 0-5% off) is that several split points can yield runtimes very close to optimal and thus small estimation inaccuracies can lead to a sub-optimal choice.

5.6 The benefits of model reuse
Figure 12 shows the additional speed-up on top of HAPI that is brought by reusing the model already present in the GPU memory in the COS across different requests, rather than loading the model for every requests. The figure shows averages across at least 4 runs. Sensitivity to model reuse is practically relevant because in a compute-constrained environment like the storage tier it may not be possible to keep all models in memory especially in the practical case when many models are trained simultaneously. This experiment also sheds light on a non-obvious interplay between several factors that influence performance: model execution time, model size and training batch size.

The key insight from this figure is that the benefit of model reuse is dependent on the specific model being used and is correlated with how prominent the model loading overhead is as part of the total processing time spent server-side for a request. When the model loading time constitutes a large portion of the total processing time, eliminating this overhead results in a more significant speed-up. Table 4 shows for HAPI BS 128 the percentage of time spent in loading the model for a request (we discard split 0 because a model is not loaded in that case). AlexNet shows the largest percentage (77%) and that correlates with the larger speed-up in Figure 12. Vgg11 and Vgg19 follow with both the percentage in the Table 4 and speed-up in Figure 12.

A few clarifications are necessary to provide a deeper understanding of the results and their implications. First, the speed-up is not proportional to the percentages in the table. This is due to several factors: (1) a faster server-side computation does not necessarily translate into equal improvements in total runtime (i.e., the client side may take a longer time and thus dictate the overall runtime) and (2) at higher batch sizes concurrency plays an additional role. Second, without the cost of model loading, HAPI may decide on a different split point. For example, for Vgg11 BS 512, HAPI with model reuse splits at 11 while without reuse it falls back to NoSplit. Similarly, for AlexNet BS 128, with model reuse it splits at 16 and without reuse it falls back to NoSplit. Interestingly, in both of these examples, HAPI falls back to NoSplit in order to avoid the impact of loading the model server-side.

5.7 Sensitivity to network bandwidth
Figure 13 illustrates at the same time (1) the influence of the network bandwidth between the server and the client and (2) HAPI’s dynamicity in choosing a split point. For this experiment we chose one specific configuration, DenseNet with BS 128. For reference, the figure shows also the performance of NoSplit.
### Table 4: The duration and % of time spent in model loading as part of the total per-request server processing time.

| MODEL   | AlexNet | ResNet18 | ResNet50 | DenseNet | Vgg11  | Vgg19  | Transformer |
|---------|---------|----------|----------|----------|--------|--------|-------------|
| total   | 0.387   | 0.048    | 0.113    | 0.096    | 0.838  | 0.811  | 0.382       |
| proc.   | 0.500   | 0.242    | 0.346    | 0.481    | 1.511  | 1.499  | 0.906       |
| % time  | 77      | 20       | 33       | 20       | 55     | 54     | 42          |

The key insight is that HAPI adapts the split point to the network bandwidth. It splits at a layer with a larger output size (split 9) for large bandwidth and at a layer with a smaller output size (split 19) when the bandwidth is scarce. Since the network bandwidth is just one factor in HAPI’s decision, the split layer’s output size does not strictly decrease with bandwidth. At around 0.5 Gbps, HAPI temporarily falls back to NoSplit as it finds that to be the best option. The gap between HAPI and NoSplit is largest in the extremes. At low bandwidth, the gap keeps increasing as NoSplit sends more data from the COS to the client. At high bandwidth, the gap grows initially and then remains constant as the network time becomes insignificant.

### 5.8 The benefits of server-side concurrency

HAPI benefits from increased concurrency on the server-side enabled by the combination of lightweight requests and batch size adaptation. The benefits heavily depend on model properties, often in a non-obvious manner. This experiment shows a deeper analysis. Figure 14 illustrates the performance gain due to concurrency. To decouple the benefits of concurrency from the splitting algorithm, the figure focuses on server-side speed-up. More precisely, it shows how much faster all requests in an iteration complete when running with a concurrency of 2 or 4 compared to sequentially (concurrency of 1). We consider that all requests complete when the data for the last request in the iteration is received by the client. To obtain a concurrency of 1, 2 and 4 we varied the batch size from 128 to 256 and 512. The grey bars show speed-up with a concurrency of 2 and the colored bars with a concurrency of 4.

The key insight is that the benefit of concurrency is a function of the split layer output sizes (via the output-related overheads of pickling, network transfers, etc.) relative to the time spent in the forward pass. The output related overheads benefit from parallelization as they are handled by either the CPU or the network. The forward pass is not parallelizable on the Nvidia T4 GPU as it is time-shared.

In Figure 14, the x-axis shows splits and not batch sizes. We chose 4 splits for each model and ordered them by increasing index for each model. The different colors for concurrency 4 represent different layer output sizes. Where possible, for each model (except Transformer), we selected the first and last split of a particular size. This keeps output-related overheads constant while the forward pass time increases.

The speed-up always drops as the split index grows. The reason for this trend is that, as the split approaches the freeze point, the overheads are low (layer output size is small or minimal) and the forward pass time is largest. Thus, the parallelizable part is smallest. The same effect can be observed by comparing two splits of the same color for a single model. In this case, the overheads are constant (same output size) but the forward pass time grows as the split index increases.

Across models, the speed-up is greatest for AlexNet since it has the shorter forward pass time. The red color (first two splits for Vgg11 and Vgg19) represents the split point with the largest output size. This explains the increased speed-up for Vgg11 and Vgg19 despite these models not having a small forward pass time.

### 6 RELATED WORK

HAPI contains a unique combination of context (COS), workload (TL), and design decisions (splitting a DNN between cloud tiers, batch size adaptation). While related work exists...
in these directions, HAPI is the first to combine them in a single cohesive system.

Batch size adaptation in ML. Dynamic adaptation of the training batch size during training was shown [63, 65, 74] to reduce training times without loss in accuracy. These ideas are complementary to HAPI’s server-side batch size adaptation because they can be applied in HAPI’s training phase on the client side. The key insight in HAPI is that during the same iteration, it is useful to configure different batch sizes for feature extraction compared to training.

Splitting ML compute between clouds/tiers. Neurosurgeon [43] splits ML inference between the cloud and edge devices to achieve low latency, low energy consumption, and high data center throughput. The partitioning is automatic and adapts to dynamics in server load and network bandwidth. Compared to Neurosurgeon, besides considering a more complex application (i.e., TL), HAPI dynamically manages storage-side concurrency via batch size adaptation. NDPipe [45] is a parallel effort to ours focusing on accelerating training and inference for image data by using near-data processing techniques to photo storage servers equipped with inexpensive commodity GPUs. HAPI differs in several technical aspects, notably by analyzing concurrency in the COS, proposing storage-side batch size adaptation, avoiding OOMs and by fine-tuning without impacting the accuracy.

Offloading compute to storage. Work on pushdowns to COS focuses on leveraging the limited subset of SQL supported by Amazon S3 Select-like systems. PushdownDB [75] analyzes which DBMS primitives can be cost-effectively moved into S3 and how more complex operations (e.g., joins) can be re-implemented on top of S3. FlexPushdownDB [73] introduces separable operators that combine data from caches with results from pushdowns. Other work analyzes pushing down computation to storage tiers not limited by S3 Select-like APIs. Rhea [25] uses static analysis of Java bytecode to generate storage-side filters for Hadoop applications. Rhea also mitigates the network bottleneck to storage but targets a different workload, does not split an application and is not concerned with OOMs. NeSSA [59] filters training data in FPGA-based SmartSSDs, transferring out relevant data subsets that result in comparable training accuracy to the full dataset. This technique is complementary to HAPI which trains on the entire dataset. DDS [76] offloads DBMS read operations to DPUs, reducing latency and CPU usage on storage servers.

Mitigating I/O bottlenecks. Recent works such as Fluid [30] and SiloD [77] focus on reducing I/O bottlenecks in cloud-based AI training. They emphasize on efficient management of storage and compute resources and on improving data access latency through advanced caching and scheduling techniques. In contrast, HAPI addresses the I/O bottleneck using a different approach by directly minimizing data movement by offloading computation to the storage layer.

Model, pipeline and tensor parallelism. Splitting in HAPI resembles model [17], pipeline [35, 37, 56], and tensor [53] parallelism, which aim to distribute the training of large models across GPU clusters. Recent systems like Aceso [52], AutoPipe [35] and Tenplex [53] further advance these strategies. Meta’s Glow compiler [62] partitions models across accelerators while applying compiler optimizations and code generation techniques. HAPI differs from these parallelism approaches in several key ways. Its primary objective is to mitigate the COS network bottleneck by splitting TL’s feature extraction phase. The concerns differ as HAPI handles multiple clients concurrently storage-side using batch size adaptation, and there is no backpropagation between HAPI’s client and server.

Data ingestion pipelines. The feature extraction phase in HAPI resembles data ingestion/pre-processing pipelines [29, 40, 54, 67, 78] because of their goal (data preparation) and the critical focus on efficiently delivering data for training. However, these pipelines are far more general in nature (e.g., can even run user-defined functions [54]) and can be very large (e.g., serve data at TB/s [78]), which makes them challenging to run entirely inside the COS. SOPHON [67] offloads specific pre-processing tasks to remote storage. In HAPI, because the feature extraction phase is part of the DNN, it needs to be optimized as part of the training job with fewer knobs compared to full-fledged pipelines.

Related optimizations. DeepPlan [41] and PipeSwitch [5] are complementary works to HAPI that optimize model loading from host to GPU memory and can be applied to HAPI servers when model reuse is not possible. Intel’s OpenVINO Toolkit [81] optimizes inference by applying hardware-specific optimizations. OpenVINO can accelerate and improve the efficiency of HAPI’s feature extraction phase.

7 DISCUSSION AND FUTURE WORK

Impact of features/limitations of COS platforms. Certain features and limitations of COS platforms can facilitate or hinder HAPI’s performance and implementation. The faster the storage-side GPU is, the better the runtime of the pushdown becomes. A fast storage medium for TL inputs can mitigate potential storage bottlenecks when feeding those inputs to the DNN pushdown and thus the storage-side GPU bandwidth can be efficiently utilized. Though not always available in the COS, storage and network-level bandwidth isolation between pushdowns and regular data transfers (i.e., transfers out of the COS that do not involve pushdowns) would help increase the predictability of pushdowns.
Automating model splitting. In future work, we aim to automate the model customization process for DNNs to enable them to run the forward pass between arbitrary start and end layers, allowing computation to be split at any chosen layer. This involves automatically analyzing the model’s computational graph to detect layers involved in non-sequential dependencies, such as skip connections or residuals, ensuring safe model partitioning without manual intervention. In PyTorch, this can be achieved by leveraging tools like torch.fx to trace the graph and identify dependencies.

Efficient parameter fine-tuning methods. While our work focuses on traditional fine-tuning methods in TL, recent advances in efficient parameter fine-tuning, such as low-rank adaptation (LoRA) [34], and quantization techniques [19, 50] have shown significant promise in reducing the number of trainable parameters and computational requirements while preserving model performance. These techniques are particularly useful for large-scale models and resource-constrained environments. Given that, for the moment, HAPI only considers freezing early layers and limiting backpropagation to later stages, adapting these methods is not straightforward. We plan to investigate how such approaches could be integrated into a storage-disaggregated architecture.

8 CONCLUDING REMARKS

HAPI is a transfer learning (TL) fine-tuning system that spans the compute and COS tiers and introduces two new techniques that address challenges introduced by storage disaggregation. HAPI judiciously splits the DNN between tiers by pushing down to storage part of TL’s feature extraction phase. This mitigates the cloud network bottleneck and also reduces training time by carefully balancing processing time across tiers. Crucially, splitting also decouples the batch size used during the training and feature extraction phases, facilitating the use of batch size adaptation in the COS without affecting the overall training accuracy. This enables increased pushdown concurrency by greatly reducing the amount of memory necessary for the pushdowns. HAPI yields up to 2.5× training speed-up while choosing in 86.8% of cases the best performing split point or one that is at most 5% off from the best.

ACKNOWLEDGMENTS

We thank our shepherd, Pankaj Mehra, and the anonymous reviewers for their insightful comments. This work has been partially funded by a research grant from the Huawei Munich Research Center, Germany.

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