Speeding up Deep Learning with Transient Servers

Shijian Li Robert J. Walls Lijie Xu† Tian Guo
Computer Science, Worcester Polytechnic Institute
Institute of Software, Chinese Academy of Sciences†
{sli8,rjwalls,tian}@wpi.edu, xulijie@iscas.ac.cn

Abstract

Distributed training frameworks, like TensorFlow, have been proposed as a means to reduce the training time of deep learning models by using a cluster of GPU servers. While such speedups are often desirable—e.g., for rapidly evaluating new model designs—they often come with significantly higher monetary costs due to sublinear scalability. In this paper, we investigate the feasibility of using training clusters composed of cheaper *transient* GPU servers to get the benefits of distributed training without the high costs.

We conduct the first *large-scale* empirical analysis, launching more than a thousand GPU servers of various capacities, aimed at understanding the characteristics of transient GPU servers and their impact on distributed training performance. Our study demonstrates the potential of transient servers with a speedup of 7.7X with more than 62.9% monetary savings for some cluster configurations. We also identify a number of important challenges and opportunities for redesigning distributed training frameworks to be transient-aware. For example, the dynamic cost and availability characteristics of transient servers suggest the need for frameworks to dynamically change cluster configurations to best take advantage of current conditions.

***Index Terms*—Distributed deep learning, performance measurement, cloud transient servers**

I. Introduction

Distributed training is an attractive solution to the problem of scaling deep learning to training larger, more complex, and more accurate models. In short, distributed training allows models to be trained across a cluster of machines in a fraction of the time it would take to train on a single server. For example, researchers at Facebook achieved near linear scalability when training a ResNet-50 model on the ImageNet-1k dataset using 32 GPU-equipped servers [**?**].

Distributed training is especially attractive for companies that want to leverage cloud-based servers. All major cloud providers—Google, Microsoft, and Amazon—offer GPU server options to support deep learning. However, existing distributed training frameworks make traditional assumptions about the lifetime of cloud servers in its cluster. Namely, that once a server is acquired by the customer it will remain available until *explicitly* released back to the cloud provider by that customer. In this paper, we refer to such servers as *on-demand*. While this assumption is reasonable for many deployments, we argue that it also represents a missed opportunity.

		Training time (hours)	Cost ($)	Accuracy (%)
Training Setup	*4 K80 transient*	(1.05, 0.17)	(1.05, 0.02)	(91.23, 1.30)
	1 K80 on-demand	(3.91, 0.03)	(2.83, 0.02)	(93.07, 0.002)
	4 K80 on-demand	(0.99, 0.02)	(2.92, 0.05)	(91.20, 1.01)
Transient revocation scenarios	*r = 0 (21 out of 32)*	(0.98, 0.01)	(1.04, 0.01)	(91.06, 1.43)
	r = 1 (8 out of 32)	(1.13, 0.12)	(1.07, 0.01)	(91.83, 0.90)
	r = 2 (2 out of 32)	(1.45, 0.50)	(1.10, 0.02)	(90.68, 0.30)

TABLE I: ***Benefits of transient distributed training.*** *On average, training with 4 K80 transient GPU servers achieve 3.72X speedup with 62.9% monetary savings, compared to running on one K80 on-demand GPU server. In addition, we observe at least 1.2% accuracy drops compared to single GPU server training. However, the slightly lower accuracy is due to training on stale model parameters in distributed asynchronous training. That is, training with 4 K80 servers, regardless of transient or on-demand, produce models with almost identical accuracies. Here r = x (y out of 32) denotes that the revocation of x workers happens in y clusters. Performance metrics are represented in a tuple of average and standard deviation throughout the paper, unless otherwise specified.*

In this work, we ask the question: what if we use *transient* rather than *on-demand* servers for distributed training. Transient servers offer significantly lower costs than their on-demand equivalents with the added complication that the cloud provider may *revoke* them at ~~anytime—violating~~ any time—violating the availability assumption discussed in the preceding paragraph. Google, Microsoft, and Amazon all offer transient servers, so the idea of distributed training with transient servers is applicable to all three major cloud platforms

Consider the following motivating experiment. Using a single on-demand GPU server on Google Compute Engine, we were able to train a *ResNet-32* model in 3.91 hours with a total cost of $2.83 on average (Table I). When we use distributed training with four on-demand servers—with each machine identical to the single server used the in previous runs—we improved the average training time to 0.99 hours with similar overall cost of $2.92. Finally, when we use distributed training with four *transient* servers we retain the improvement in training time, 1.05 hours on average, while significantly reducing the total cost to $1.05 on average (Figure 1). We saw these performance increases even though we made no significant modifications to the distributed training frameworks and 13 of the 128 transient servers (affecting 11 out of the 32 clusters) were revoked at some point prior to the completion

of training. We provide a more detailed analysis of this experiment and the impact of server revocation in Section III.

Our goal is to identify the important design considerations needed for rearchitecting distributed training frameworks to support transient servers. While the simple experiment above demonstrates the potential of distributed training with transient servers (e.g., reduced training time and cost) as well as the challenges (e.g., server revocation and availability), we believe that transient servers also offer additional opportunities. For example, price dynamics make it more attractive to use clusters with machines drawn from multiple, geographically-diverse, data centers. Such an approach raises interesting questions about the impact of communication costs and latency on training performance. Similarly, rather than use a cluster composed of servers of the same type, we might employ heterogeneous clusters composed of machines with different computational resources and capabilities. Finally, the clusters themselves need not be static; instead, we might dynamically add or remove servers to make distributed training more robust to server revocation or to take advantage of volatile server pricing.

We conduct the first *large-scale* empirical measurement study that quantifies the training performance of deep learning models using cloud transient servers. Through our study, we make the following additional contributions:

- We compare the training time and cost of distributed training using transient servers to on-demand servers. We observe up to 7.7X training speedup and up to 62.9% monetary savings in one of the distributed training ~~experiment~~ experiments when compared to the single GPU baseline.
- We quantify the revocation impacts of transient servers on training performance and identify the importance of larger cluster sizes and the need to redesign distributed training frameworks. In addition, our observations about model accuracy reveal the opportunities for mitigating revocation impacts if cloud providers were to support *selective* revocation.
- We also demonstrate the benefits and limitations of using heterogeneous servers in distributed training. In particular, our findings suggest a number of plausible transient-aware designs for deep learning frameworks, including the ability to train with dynamic cluster sizes, to better exploit these cheap transient servers.

II. Background and Motivations

In this section, we first provide necessary background on distributed training that motivates our selection on parameter server-based asynchronous training in Section II-A. Then we explain the opportunities and challenges presented by training with transient servers in Section II-B. An overview of transient-based distributed training is illustrated in ~~Figurre~~Figure 2.

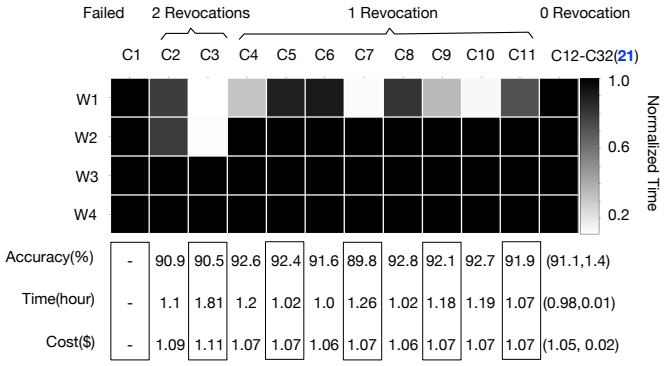


Fig. 1: ***Quantifying distributed training performance using transient servers.*** *We launched 32 transient GPU clusters for training ResNet-32 model on Cifar-10 dataset. Each cluster C_i is configured with four* `K80` *transient GPU servers($W1$ to $W4$) and one parameter server. We observe that 21 out of 32 transient clusters completed training with 0 revocation, and that 13 out of 128* `K80` *transient servers were revoked during various training stages—the lighter the shade, the earlier the revocation. On average, training with 4* `K80` *transient GPU servers achieve 3.72X speedup and 62.9% monetary savings, compared to running on one* `K80` *on-demand GPU server.*

A. Distributed Deep Learning

In this paper, we focus on evaluating distributed training with parameter server-based asynchronous training due to its popularity and potentially more resilient to training server failures. The concept of distributed deep learning on multiple GPU servers is relatively new [**?**], and a number of frameworks such as TensorFlow [**?**] and FireCaffe [**?**] have started to support training DNN models in multiple network-connected GPU servers (not just single server with multiple GPUs).

Conceptually, the training of a convolutional neural network can be divided into four phases. First, the model parameters are initialized, often randomly or with a popular function such as Xavier [**?**]. Second, one batch of input data is selected and the feed-forward computation is performed at each layer l by applying the function on the weights, inputs, and the bias term from the previous layer $l-1$. The computation stops when the output layer is reached and the results are recorded. Intuitively, this second phase is identical to the process of generating predictions using a trained model. Third, model errors are calculated by comparing the probability distribution (i.e., the model output) generated for each input to the known true value and multiplying by the derivative of the output layer. The errors are then propagated from layer l to its previous layer $l-1$ until reaching the first layer. Fourth, the model parameters between layer $l-1$ and layer l are updated by multiplying the learning rate and the gradient of layer l and weights at layer $l-1$.

As the model gets bigger—i.e., more parameters and computation-intensive layers—the training time also increases. To speed up the training process, the phases two through four above can be distributed across different servers to parallelize training. A common way to do so is to have a parameter server [**?**], [**?**] that is in charge of updating model parameters

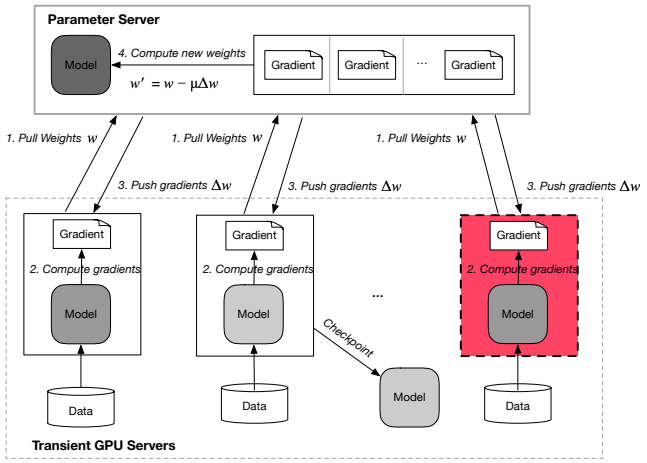


Fig. 2: ***Illustration of distributed training on transient GPU servers.*** *We adopt an asynchronous distributed training architecture. The parameter server runs on an on-demand CPU server and the workers (including a special master that is in charge of model checkpointing) run on transient GPU servers. Workers are in charge of calculating the gradient updates while the PS incorporates the gradients to update the model parameters. The training can still progress even if some of the workers, e.g., red box, are taken away by cloud providers.*

(phase four), and a cluster of powerful GPU servers to work on the forward and backward propagation (phases two and three). It is worth noting that phase two is the most ~~time consuming~~ time-consuming of the training process [**?**] and, therefore, would enjoy the largest benefit from adding more GPU servers.

In this paper, we adopt the asynchronous distributed training architecture depicted in Figure 2. Here each worker keeps an entire copy of the model and independently calculates gradients using its local copy of the input data—this also referred to data-parallelism.[1] In addition, each worker can pull the most-recent model parameters from a parameter server without needing to wait on the parameter server to collect and apply gradients from all other workers, i.e., asynchronous training. It is also possible to use more than one parameter server, in which case each worker needs to contact all parameter servers (not depicted in the figure). Consequently, workers might be working on slightly outdated models (indicated by different shades in Figure 2); this model staleness can lead to a reduction of model accuracy. Currently, in TensorFlow distributed training, one master worker will also periodically save the model parameters. Even if one of the workers fails—e.g., the last worker colored with red in Figure 2—the training can still progress, albeit at a degraded speed. However, if the master fails, the distributed training also fails because we will not have access to the model files with the converged accuracy.

B. Transient Servers

Transient servers are cloud servers that are offered at discounted prices (up to 90% cheaper). Major cloud providers, such as Amazon EC2 and Google Compute Engine (GCE), offer transient servers in the form of spot instances and preemptible VMs. Unlike traditional *on-demand* servers, cloud providers can take back transient servers from customers at any time [**?**], [**?**]. When such situations arise, customers are only granted a short time window—30 seconds for GCE and 2 minutes for EC2—before permanently losing access to the server. This is often referred to as *server revocation*.

Aside from revocation, transient servers offer the same performance as equivalently configured on-demand servers. For example, the training performance with *4 K80 transient* servers when *r=0* (no revocations) and training with *4 K80 on-demand* servers are almost identical, see Table I.

Cloud transient servers exhibit three key characteristics that make them both beneficial and challenging to leverage for distributed training.

First, transient servers are significantly cheaper allowing customers to devote additional servers to training, speeding up the training time while remaining within a fixed monetary budget. Depending on whether the transient servers are statically priced (e.g, GCE preemptible VMs) or use a more dynamic pricing model (e.g., Amazon spot instances), cloud customers have a range of possible cluster configurations, e.g., number of servers, that may evolve over time. For instance, in the case of dynamic pricing, cloud customers will need to regularly monitor prices and adjust the cluster configuration to maximize training performance and reduce costs.

Second, the availability of transient servers, compared to their on-demand counterparts, can be lower or even unpredictable. Here the availability of cloud servers refers to the probability of cloud providers fulfilling the resource request in a timely manner. Availability depends, in part, on the overall demand for servers (both on-demand and transient) in the local region [**?**]. Therefore, to best utilize transient servers it is likely that customers will need to request servers with different (but more available) resource capacities and from multiple regions.

Third, transient servers have uncertain lifetimes. Here a server's lifetime is the time interval between when the cloud provider satisfies the customer's request for a new server and the time the server is revoked. Different cloud providers have different policies that directly affect server lifetimes. For Google Compute Engine, the maximum lifetime of any transient server is at most 24 hours. That is, even though GCE preemptible VMs can be revoked at any point, they are guaranteed to be revoked after 24 hours.

We empirically measured the lifetime of GCE transient servers (with the configurations detailed in Table II). Our measurement involves more than 600 transient servers that were requested at different time-of-day, from different data center locations, and with different levels of resource utilizations. In Figure 3, we compare the lifetimes of GCE transient servers. We observe that different GPU servers have different revocation patterns, and that even though up to 70% servers can live up to 24 hours, about 20% of them are revoked within the first two hours—in such cases, distributed training that lasts more than two hours will be subject to revocation impacts.

[1]For training with large volumes of data, the data are also often divided into shards.

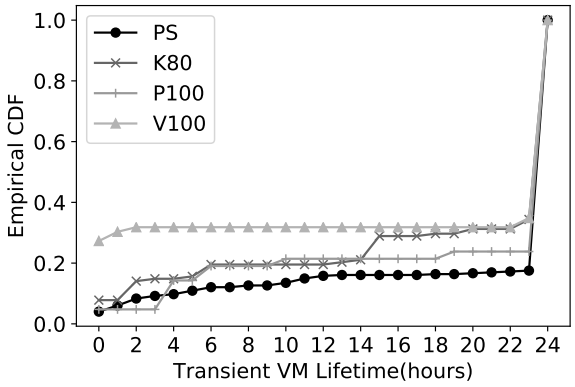


Fig. 3: ***CDF of Google preemptible GPU servers lifetime.*** *We measure the lifetime as the time between when the preemptible GPU servers are ready to use and when the servers are revoked by the Google cloud platform. Note that Google transient servers have a maximum lifetime of 24 hours. We observe that less than 20% of transient servers are revoked in two hours.*

GCE instance	Mem. (GB)	vCPU	On-demand ($/hr)	Transient ($/hr)	Saving potential(%)	EC2 counterpart
K80	61	4	0.723	0.256	35.4	p2.xlarge
P100	61	8	1.43	0.551	38.5	-
V100	61	8	2.144	0.861	40.2	p3.2xlarge
PS	16	4	0.143	0.041	-	m4.xlarge

CNN model	Num. parameters	Model size (MB)	Num. layers	Batch size	Top-1 accuracy(%)	Optimizer
ResNet-32	1.9M	14.19	32	128	92.49	Momentum

TABLE II: ***Server configurations and models used in our experiments.*** *We customized both GPU servers (used to run workers) and a CPU server (shaded and referred to as PS) in Google Cloud Engine. The first column specifies the type of GPU cards used for each server. For* ResNet-32*, the top-1 accuracy is obtained from the original paper that evaluates against Cifar-10 dataset.*

In summary, cloud transient servers present an opportunity to speed up deep learning with cheaper server resources. However, considering the potential revocations and unavailability of transient servers, leveraging these resources requires us to rethink existing techniques for distributed training. Current distributed frameworks, designed with stable on-demand servers in mind, do not adequately support the features that are necessary for leveraging transient servers; e.g., dynamic cluster adjustment, robust model checkpointing, or support for heterogeneous and geographically distributed clusters.

III. Experimental Evaluation

Our evaluation focuses on answering the following key research questions: (1) How do transient servers compare to on-demand servers with respect to distributed training? (2) What is the best cluster configuration given a fixed monetary budget? (3) How does revocation of transient servers impact distributed training? (4) What are the potential benefits and challenges associated with dynamic clusters? (5) What is the performance impact when using heterogeneous server resources?

A. Experimental Setup

a) Public Cloud Infrastructure: We conducted our experiments using Google Compute Engine (GCE) and the server configurations are shown in Table II. We choose three GPU server configurations with different GPU capacities—`K80`, `P100`, and `V100` in increasing order of GPU memory, parallel cores, etc. For simplicity of exposition, we refer to each GPU server configuration by the attached GPU.

To better avoid memory and CPU bottlenecks in our evaluation, we choose the max memory and virtual CPU values allowed by GCE for each configuration.

The *saving potential* illustrates the cost difference between *transient* and *on-demand* instances. It is calculated as the unit on-demand price divided by the unit transient cost.

The fourth server in Table II, labeled `PS`, was used to run the parameter server during distributed training. This server did not have an attached GPU—hence, the reduced cost—and was also run using an on-demand instance. The reason we use an on-demand instance for the parameter server for distributed training is to circumvent the checkpoint restarts that would result if parameter server is revoked. However, we do use transient parameter servers when measuring the lifetime of transient CPU server.

b) Deep Learning Framework: We leveraged the popular deep learning framework TensorFlow [**?**] for all our experiments given the relative maturity of the project and support for distributed training. We also used the Tensor2tensor library [**?**] to assist in the training process.

For the model, we selected ~~*RestNet-32*~~*ResNet-32* [**?**], in part, due to its popularity. This CNN model can be trained to convergence using a single GPU server in ∼4 hours, making it practical for our experiments. See Table II for full model details.

For the training dataset, we used, *Cifar-10* [**?**], a standard image recognition dataset consisting of 60K color images, each 32 by 32 pixels, spanning 10 output classes. Following standard conventions in the field of deep learning, we used 50K images for training and the rest for testing. We also used the same hyperparameter configurations (e.g., learning rate) as specified in the original paper for most of our experiments—any differences are noted when appropriate.

c) Performance Metrics: We focus on performance metrics that are most relevant to comparing distributed training on transient servers to training on on-demand servers. For transient servers, we monitor the revocation events and record their lifetimes respectively. For transient servers that were revoked by GCE, their recorded lifetime will typically be shorter than the total training time for the cluster. Finally, a training cluster is said to have *failed* if the master worker is revoked prior to training completion.

For distributed training, we measure training time, training cost, and accuracy. Training time is defined as the amount of time required to complete the specified training workload. When training the ~~*RestNet-32*~~*ResNet-32* model, we specify the training workload to be *64K* steps where each step equates to processing a batch of 128 images in the *Cifar-10* dataset. We refer to the model generated at *64K* steps as a *converged model*.

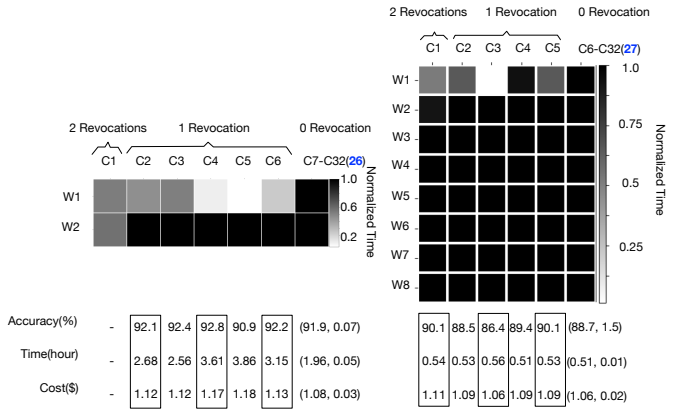


Fig. 4: ***Performance comparison between distributed training using transient and on-demand GPU servers.*** *We measure the distributed training performance with three different cluster sizes. We repeat each cluster size 32 times and label them as C_i where $i \in [1, 32]$. The cluster runs are sorted by the number of revocations and the workers W_j are sorted by their lifetime. On average, using transient servers can achieve up to 62.9% cost savings and up to 7.7X training speed up when compared to training using one* `K80` *on-demand server. In all cases of distributed training with transient servers, the converged accuracy is comparable to that of on-demand distributed training.*

Training cost is calculated using the sum of all cloud servers that participate in the training process. In the case of distributed training, these include GPU servers that are responsible ~~of~~ for calculating the gradients and the CPU server that is in charge of updating the model parameters. We calculate the cost of each server by multiplying the unit cost by the amount of time that server was active in training. For a transient server, the active training time stops when the server is revoked or the training has completed. When analyzing the training cost, we use a fine-grained second-based charging model [**?**]. For example, if the active training time is 3601 seconds, we will charge the server for 3601 seconds. In the traditional hour-based charging model, the cost would instead be based on two hours. Regardless of the charging model, we can amortize the cost effectively when transient training is offered as a service in which different training sessions can share the training servers.

Training accuracy is measured as the top-1 accuracy, i.e., the percentage of correctly predicted images using the trained model on the test portion of the dataset. In the case of the ~~*RestNet-32*~~*ResNet-32* model, we evaluate accuracy after *64K* steps. While our goal is not to increase the accuracy of existing models, it is important to demonstrate that distributed training with transient servers does not have a significant negative impact on accuracy.

B. Transient vs. On-demand Servers

For our first experiment (first described in the introduction), we evaluate the *feasibility* of using transient servers for distributed training as opposed to the traditional, more expensive, and more available on-demand equivalents. Specifically, we launched 32 transient GPU clusters for training the *ResNet-32* model on the *Cifar-10* dataset. Each cluster C_i was configured with four-`K80` transient GPU servers and one parameter server `PS`. Our on-demand clusters used the same configuration.

From Table I, we observe that distributed training offers a significant reduction in training time and that distributed training with transient servers further offers a significant reduction in cost. More concretely, the speedup is up to 3.72X when using clusters that fit within the initial budget for a single `K80` on-demand server. Moreover, we see a 62.9% saving in training cost with slightly degraded top-1 accuracy (∼1.2%) at convergence time. The slightly lower accuracy is due to training on stale model parameters in distributed asynchronous training and affects transient and on-demand clusters *equally*.

Our empirical analysis reveals three other important observations. First, even with server revocation transient servers offer tangible benefits over distributed training using on-demand servers; namely, significantly lower cost with similar accuracy at the cost of 5.7% longer training time. More concretely, we observed 13 server revocations in 11 of our 32 transient clusters. In all but one case, the training continued after revocation and finished successfully with an average speedup of 3.72X and cost savings of 62.9%. Figure 1 illustrates the observed revocations for the transient clusters. The caveat here is that the revoked servers cannot be the master server for the cluster, hence our next observation.

Second, current distributed training architectures need to be *redesigned* to support the failure of the server responsible for checkpointing, i.e., the master. Currently, if the master GPU server is revoked (happened once in our 32 runs for this experiment) then the distributed training will fail.

Third, the number of revoked GPU servers had little impact on the training cost and accuracy but increased training time (up to 48%). This implies that we could mitigate the revocation impact on distributed training performance by increasing the cluster size. We empirically evaluate this hypothesis in the following sections.

Summary: Distributed training with transient servers can speed up deep learning by up to 3.72X with 62% cost savings, when comparing to training using on-demand servers. Our analysis motivates the need for redesigning distributed training frameworks to support more robust model checkpoint, and suggests that training with larger cluster sizes allows better tradeoffs between training time and accuracy.

C. Scaling Up vs. Out with Transient Servers

Using the cost of training on a single on-demand `K80` as a constraint, we investigate the merits of scaling up—using more powerful GPU servers—or scaling out—using a cluster of GPU servers. Intuitively, we are asking the question: what is the best cluster configuration given a fixed monetary budget?

We selected three scaling out and two scaling up transient cluster configurations, running each 32 times, and present the average performance in Table III. All clusters were able to finish within the specified monetary cost budget of $2.83.

Our results reveal three important insights. First, scaling up is less resilient to server revocations. We observed a training

Transient Training	Revocations	Time (hours)	Cost($)	Accuracy(%)
2 K80+1 PS	6.25% (28 out of 448)	(2.16, 0.50)	(1.31, 0.08)	(91.93, 0.70)
4 K80+1 PS		(1.05, 0.17)	(1.16, 0.04)	(91.23, 1.30)
8 K80+ 1PS		(0.51, 0.01)	(1.11, 0.02)	(88.79, 1.50)
1 P100	6.66% (2 out of 32)	(1.50, 0.04)	(0.83, 0.02)	(93.11, 0.24)
1 V100	43.8% (14 out of 32)	(1.23,0.04)	(1.06, 0.03)	(92.98, 0.39)

*TABLE III: **Scaling up vs. scaling out.** Under the same training cost budget constraint, we empirically measure and compare the training performance of scaling up and out using transient resources. We calculate the average performance across all training setups that completed successfully. In the scale up case, 28 (12) out of 32 runs for P100 (V100) were able to finish 64K steps. In the scale out case, training only fails when the K80 master worker is revoked with a probability of 6.25%. Although K80 clusters with various sizes have the same complete failure probability, the larger the cluster size, the less revocation impact it is. This is because the probability of two K80 servers being revoked is the same for cluster of size n, but if $n = 2$, that equals to the failure case while if $n = 8$, the training can still progress albeit at a degraded performance compared to the initial cluster.*

		Avg. revocation overhead (%)			Distributed training performance		
Revocation scenarios	Cluster Size	Training time	Cost	Accuracy	Training time (hours)	Cost ($)	Accuracy (%)
r = 0	2	-	-	-	1.96	1.28	91.90
	4	-	-	-	0.98	1.14	91.06
	8	-	-	-	0.51	1.11	88.65
r = 1	2	61.7	14.8	0.18	3.17	1.47	92.08
	4	15.3	3.5	0.77	1.13	1.18	91.83
	8	3.9	2.7	0.05	0.53	1.14	88.60
r = 2	2	-	-	-	-	-	-
	4	48	9.6	0.38	1.45	1.25	90.68
	8	5.9	5.4	1.45	0.54	1.17	90.10

*TABLE IV: **Quantifying revocation overhead for different cluster sizes.** With the same revocation scenarios, i.e., $r = i$ where i is the number of GPU servers that were revoked during the training session, the impact on training time and cost decreases with increases in cluster size. In addition, with the same initial cluster size, we observe higher revocation overheads the greater the number of revocations.*

failure rate of 6.66% for the P100 and 43.8% for the V100 compared to just 3.1% for a cluster of K80 machines. The lifetime of revoked server during distributed training ~~are~~ is depicted in Figure 1, as well as Figure 4. Note, for the two former configurations with a single machine, the server revocation and training failure rates are the same.

Second, increasing the size of the cluster improves training speed but reduces the accuracy of the trained model. For instance, scaling out to 4-K80 cluster is 30% (and 14.6%) faster when compared to scaling up to one P100 (or V100, respectively) with slight decrease of 1.75% accuracy.

Third, the decrease in accuracy is non-linear as the cluster increases. We observe a significant drop of 4.28% in accuracy when the cluster consists of 8-K80 servers. We also observed that the accuracy converges before 64K steps, i.e., prolonging the training does not improve the accuracy. These observations are consistent with previously noted impacts of stale model parameters on the converged accuracy [**?**], [**?**], [**?**], [**?**].

Summary: When configuring the transient server clusters, one needs to consider various factors, including revocation probability, training time reductions, and desired model accuracy. Based on our measurements, a cluster size of four balances the above factors for our target model.

D. Revocation Impact

As summarized in Table IV, the impact of server revocation depends on the size of the training cluster. Here the revocation overhead is calculated by comparing the average performance achieved in each revocation scenario to equivalent cluster *without* any revocations. For both training time and cost, the revocation overhead decreases with increased cluster size. For example, for the 8-K80 cluster, the overhead of a revocation is only 3.9% for training time and 2.7% for training cost.

Together with the lifetime of revoked GPU servers in Figure 1 and Figure 4, the reduced overhead observed in the larger cluster is a combination of two factors: transient servers being revoked at different stages relative to the cluster training time (albeit the actual lifetime might be the same) and the percentage of lost computation power relative to the cluster capacity. Note that when a worker is revoked, the lost work is equivalent to the time to generate gradients from one batch of data, in the ~~worse case~~ worst-case scenario. This implies that choosing a larger transient cluster size can be more resilient to server revocations as it reduces the time that each individual server is needed.

Interestingly, we observe a slightly increased accuracy for clusters of size two and four (shaded cells). We suspect this may be caused by losing a GPU server that happens to be slightly slower than average and is working on more stale model parameters than the rest. If true, this motivates the redesign of cloud transient server revocation. In essence, when revoking transient servers, if cloud providers could only specify the number of servers needed from a particular cloud customer and leave the choices of *which* servers to be revoked to the cloud customer, it will enable more flexibility of making tradeoffs between accuracy and the rest of the training performance.

On the other hand, as the number of revocations ~~increase~~ increases from one to two occurrences, the overhead for training time and cost also increases significantly. In the case of 4-K80 clusters, the overhead triples. Again, this indicates that in addition to the number of revocations, the timing of revocations also plays an important role in defining the revocation overhead. Although cloud customers cannot control when and how many revocations will occur during training, our results suggest strategies for reducing impact by either increasing the cluster size or selectively returning training servers thereby improving accuracy by controlling model staleness. The cost savings, up to 70% compared to a single K80, also make it possible to launch more than one transient cluster to further mitigate against the impact of revocations.

Summary: The impact of server revocation on training time and cost depends on the number of revocations, the cluster size, and when the revocation events happen. Larger cluster sizes are more resilient to revocation. Further, our observations

		Distributed training performance		
Cluster size	**Training status**	**Training time (hours)**	**Cost ($)**	**Accuracy (%)**
2	*r = 0*	(1.96, 0.05)	(1.28, 0.03)	(91.90, 0.70)
	On-demand	(1.99, 0.06)	(3.16, 0.10)	(91.90, 0.73)
4	r = 0	(0.98, 0.01)	(1.14,0.01)	(91.06, 1.43)
	On-demand	(0.99, 0.02)	(3.02, 0.05)	(91.20, 1.01)
8	r = 0	(0.51, 0.01)	(1.11, 0.02)	(88.65, 1.52)
	On-demand	(0.51, 0.01)	(3.01, 0.03)	(88.40, 2.23)

TABLE V: ***Comparison of distributed training performance using on-demand and transient servers.*** *For all three cluster sizes, we observe little performance deviations on training time (1.5%) and accuracy (0.25%) between running using on-demand and transient* `K80` *servers. However, on-demand distributed training exceeded the monetary budget by up to 11.7% (highlighted in red), casting doubt on the practicality of speeding up training with on-demand clusters.*

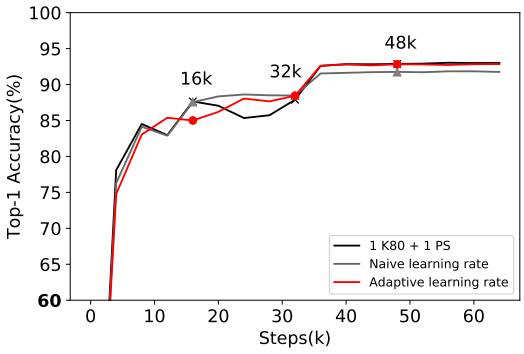


Fig. 5: ***Benefits of dynamic transient distributed training and adaptive learning rate.*** *Dynamically scaling training cluster allows training to be finished 40.8% faster compared to the static cluster. By adaptively setting the learning rate based on the cluster size, we mitigate the accuracy degradation with naively using sparse mapping.*

suggest that further improvements are possible if the cloud provider adopts a more flexible revocation policy, e.g., by allowing the customer to choose which resources get revoked.

E. Scaling Up with On-demand Servers

Here, we compare the distributed training performance between on-demand and transient clusters (without revocations) using the same number of `K80` servers. Given the limited variance in on-demand performance, we only repeat the on-demand training ten times. We present the average performance and standard deviation in Table V. Our measurement demonstrates that scaling up with on-demand servers incurs almost 2X higher training costs with almost identical training time and accuracy. This again showcases the good opportunity presented by transient servers in keeping up with on-demand training performance while being significantly cheaper.

F. Dynamic Transient Clusters

Given the extended time it can take to train a model and the relative volatility of transient server prices, it may make sense to dynamically add and remove GPU servers during training. This would, for example, allow cloud customers the flexibility to add cheaper transient servers to speed up distributed training and ensure that they always have the best server configuration given their budget and rapidly changing server prices. We refer to this concept as *dynamic transient clusters*.

As existing distributed training frameworks do not natively support dynamic clusters, we instead propose a technique called *sparse mapping* to enabling dynamically adjusting training cluster configurations during runtime. When using sparse mapping, cloud customers specify the maximum number of workers (i.e. GPU servers), referred to as slots, allowed in the cluster. These slots would then be filled *opportunistically* during training. For example, a cloud customer can initialize a cluster with four slots and start training with one initial GPU server; the other slots will be filled dynamically.

Intuitively, using sparse mapping allows cloud customers to more efficiently utilize transient servers depending on dynamic conditions, such as price. To demonstrate this, we started a cluster with a single `K80`. After every 16K steps, we added one additional `K80` server to the cluster. As shown in Figure 5, the training finishes in 2.28 hours and is 40.8% faster compared to using a static cluster size. Moreover, training with an elastic cluster also leads to 21.5% training cost savings when compared to training with the static cluster size. However, we observe 1.17% accuracy degradation for training with a dynamic cluster size. This is because an important hyperparameter, i.e., learning rate, that can affect training accuracy, is currently calculated based on the number of workers supplied in the training configuration, instead of the *active* workers. We refer to the vanilla way of leveraging sparse mapping without changing learning rate as *naive learning rate*.

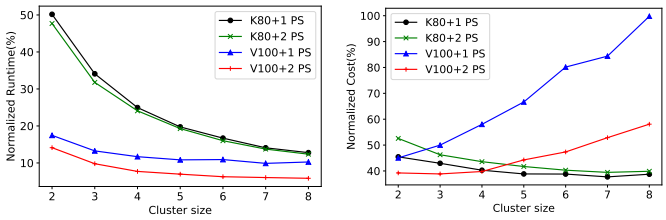
To further investigate the impact of incorrectly configured learning rate, we implement an *adaptive learning rate* that adjusts the learning rate based the number of *active* workers instead of the number of total workers (slots). In Figure 5, we compare the achieved top-1 accuracy of training with adaptive learning rate to both the baseline of training with one `K80` server and training with a cluster with increasing number of `K80` servers with naive learning rate. As shown, using adaptive learning rate can improve the converged accuracy by 1%.

Summary: Sparse mapping provides a practical way to utilize transient servers dynamically. However, naively utilizing sparse mapping can lead to model accuracy degradation due to inappropriate learning rate. But adaptively scaling learning rate to current number of workers can achieve 1% higher accuracy compared to naive learning rate.

G. Implications of heterogeneous training

As empirically demonstrated previously, different classes of transient servers exhibit different revocation probability, cost saving, and training speed trade-offs. This motivates the need to utilize a mix of GPU servers to balance such trade-offs in distributed training. We refer to such clusters as *heterogeneous* and in this section, we study two type of server heterogeneity—GPU types and server location.

We choose a cluster of *four* servers for understanding the implications of ~~heterogenous~~ heterogeneous training for



(a) Training time. *(b) Training cost.*

Fig. 6: ***Training performance bottleneck.*** *We measure the training time and monetary costs of scaling out with less powerful* `K80` *and more powerful* `V100`*, normalized to the single* `K80` *training. For* `K80` *clusters, the number of* `PS` *has little impact on the training speed. In contrast, we observe up to 1.75X training speed using 2* `PS` *in* `V100` *clusters compared to that of one* `PS`*. Consequently, the negligible speedup with using more expensive* `V100` *has lead to an almost linear increase of training cost. Note, training accuracy exhibits similar trend of decreasing with the cluster size as shown previously, and therefore we omit the accuracy comparison due to space limitation.*

two reasons. First, when scaling out with more powerful `V100`, we have observed that training time quickly plateaus after using more than four servers (Figure 6a). That is, the training bottleneck has shifted from the ability to parallelize the gradient computations to how fast the single `PS` can handle the weight pulling and gradient pushing from GPU servers. When using *two* `PS` for `V100` clusters, we again observe training speed up for up to 1.75X compared to the single `PS` scenario. Second, under the current Google Compute Engine transient pricing models, when scaling out with more powerful `V100`, the monetary cost grows almost linearly, as shown in Figure 6b.

For understanding the first type of size heterogeneity, we conduct three baseline training scenarios of *homogeneous* clusters that consist of the same GPU server types, namely `K80`, `P100`, and `V100`. Let's define the training cluster with the number of GPU servers and types as $(N_{K80}, N_{P100}, N_{V100})$, e.g., N_{K80} denotes the number of `K80` used. In this experiment, we set the total number of GPU servers to be four, i.e., $N_{K80} + N_{P100} + N_{V100} = 4$. These homogeneous cluster configurations are represented as (4, 0, 0), (0, 4, 0), and (0, 0, 4) respectively. For each homogeneous cluster, we repeat the training ten times and record the training performance. We construct three heterogeneous clusters with different mixes of all three GPU server types. For example, we use the cluster configuration (2, 1, 1) to represent a cluster with two `K80` servers and one `P100` and one `V100` each. To reiterate, one of intuitive use cases of ~~heterogenous~~ heterogeneous GPU types stems from simply unable to request for the desired transient servers.

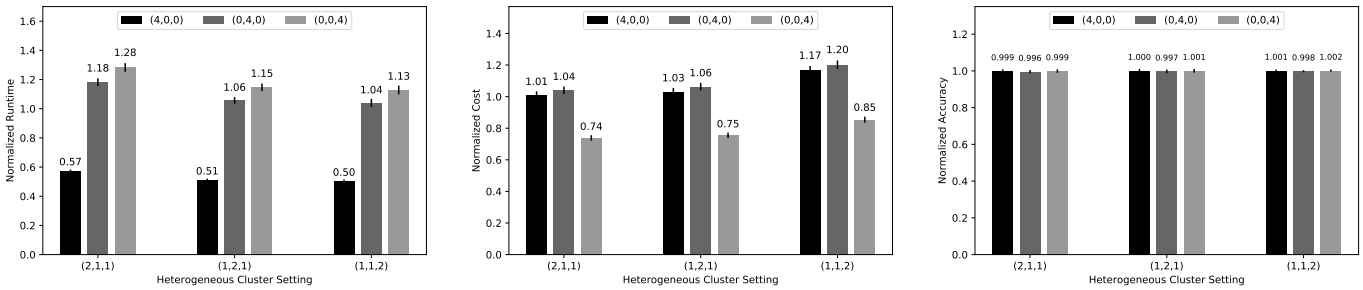
In Figure 7, we compare the training performance using heterogeneous clusters with that of homogenous clusters. When swapping out two(three) `K80` for more powerful GPU servers, we observe up to 50% speedup when compared to the homogeneous cluster of four-`K80` servers. The ~~heterogenous~~ heterogeneous training (1, 1, 2) with two `V100` incurs 17% more monetary cost. Similarly, when swapping out two(three) `V100` for less powerful GPU servers, we observe up to 28% slowdown when compared to the homogeneous cluster of four-`V100` servers. The ~~heterogenous~~ heterogeneous training (2, 1, 1) with two `K80` reduces the monetary cost by 26%. Our evaluation suggests the benefits of mixing in more powerful transient GPU servers to significantly speedup the training with manageable cost increase and negligible accuracy impact.

For understanding the second type of location heterogeneity, we compare the training performance of running distributed training within one single geographic region to across multiple regions. We choose three US based regions, i.e., *us-east1*, *us-central1* and *us-west1* and represents the cross region cluster with number of servers running in the corresponding regions. Note that `PS` is located in the data center with the largest number of workers. Similar to the need of using GPU servers of different capacities, the cost differences across regions are the key driven force for cross-region distributed training. As we can see from Figure 8, splitting the GPU servers across different regions can lead to significant slowdown, up to 48%. This is due to that GPU workers have to communicate with the `PS` through slower network connections. Even in the asynchronous training where workers do not need to wait for each other to receive the updated model parameters, the impacted workers contribute less towards completing the specified *64K* steps, effectively slow down the overall training. Additionally, we do not observe obvious slow down when splitting the training in three regions, indicating that the network connections between two data center regions have similar performance. Interestingly, there is a slight increase in accuracy as the training slow downs. This suggests the potential opportunity to mitigate impact of cross-region trainings when transient costs are low enough.

Summary: Training with heterogeneous GPU servers, either in terms of computation (size) or network (location) capacity, exhibits different tradeoffs in training cost and time. It is more intuitive to conduct distributed training with different GPU servers in the same data center, as the slow down is roughly proportional to the cost reduction. The saved money can be used to increase cluster size, therefore speedup both training and mitigate the revocation impacts. However, training across geographically dispersed data centers can incur ~~signifiant~~ significant training overhead, due to network communication. Our observations motivate the need to optimize the network communication of distributed training algorithm, in order to more effectively taking advantage of transient servers with more dynamic supply.

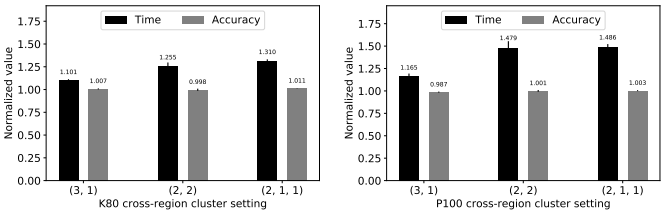
IV. Related Work

Deep learning frameworks. There are a number of deep learning frameworks [**?**], [**?**], [**?**], [**?**] that provide a composable pipeline for machine learning practitioners to design, train, validate, and deploy deep learning models. Although our measurement study is conducted on the popular TensorFlow framework [**?**], we believe the results can be extended to other frameworks such as Caffe/FireCaffe, CNTK, MXNet [**?**], [**?**],



(a) Training time. *(b) Training cost.* *(c) Training accuracy.*

Fig. 7: ***Training performance with heterogeneous server sizes.*** *Mixing workers with less powerful GPU capacities can slow down the training by up to 28% but lead to 26% cost savings when compared to training with homogenous servers. However, there is no obvious accuracy drop.*



(a) K80 clusters. *(b) P100 clusters.*

Fig. 8: ***Training performance with heterogeneous server locations.*** *Distributed training using servers from different data center locations experience up to 48% slow down when compared to training within the same region. Interesting, splitting servers in three data centers show similar performance compared to two-regions based training.*

[**?**], etc. The reason is that current deep learning frameworks share the same distributed training method, adopt parameter server to maintain training parameters, use SGD-based methods for optimizing model parameters [**?**], [**?**], and support distributed training on multi-GPU servers. However, most of current deep learning frameworks do not natively support elastically adding or removing servers while the training process is ongoing. Very recently, MXNet has embarked the efforts to dynamically scale training jobs on EC2 [**?**]. Complementary to the recent support of dynamic training, our work pinpoints the need for elasticity in transient distributed training to better utilize the dynamically available transient servers across types, regions and monetary costs.

Performance studies on deep learning. A plethora of works [**?**] have compared and studied the deep learning performance under different hardware and software configurations. In particular, researchers have investigated the scaling potentials of using CPU servers [**?**], single GPU and multi-GPU servers [**?**]. As the computation need of training deep learning grows and supports for distributed training over a cluster of GPU servers [**?**], [**?**], [**?**], prior work has factored in the impact of network communication [**?**], [**?**], [**?**] and provides initial study on tuning hyperparamters, e.g., learning rate and batch size [**?**], [**?**], [**?**], [**?**], [**?**], to mitigate the communication bottleneck and impact of stale model parameters [**?**], [**?**], [**?**], [**?**]. However, most works on distributed training performance [**?**], [**?**], [**?**] make the implicit assumptions of *static and homogenous* cluster configurations. Our study aims to understand the training performance of leveraging cheap transient servers that have dynamic availability, revocation patterns and unit costs. In addition, these previous studies often focus on measuring the training speed using the average time to process one mini-batch [**?**], [**?**], [**?**]. while in our paper, we consider important performance metrics, namely training time, cost and accuracy, that could potentially be impacted by training on transient servers.

Performance optimization based on transient servers. Since transient servers are cheaper than their counterparts, many researchers studied how to effectively running applications on cloud transient servers with as few modifications as possible [**?**], [**?**]. Some researchers proposed transient-aware resource managers [**?**], [**?**] to optimize job schedulers by taking into account the revocation rates of transient servers. Other researchers proposed system-level fault-tolerance techniques such as dynamic checkpointing to optimize the execution time of various applications including web services [**?**], [**?**], big data applications [**?**], [**?**], [**?**], [**?**] and other memory-intensive applications [**?**]. Recently, as training deep learning models can naturally benefit from more resources, DeepSpotCloud [**?**] looked at how to effectively run deep learning training by migrating from one GPU server to a cheaper transient server. Our work differs from prior works in two major ways: first, we focus on understanding how distributed training can benefit from cheap transient servers. Unlike previous commonly studied batch jobs, big data applications, or even web services, training deep learning models poses a unique trade-off of converging accuracy and training speed. Second, we explore the feasibility and quantify the benefits of performing distributed training on transient servers and identify important transient-aware design changes in distributed training frameworks in order to more effectively utilize transient resources.

V. Conclusion and Future Work

In this paper, we described the *first* large-scale empirical evaluation of distributed training using transient servers. We

compared various transient scenarios of training a popular CNN model called *ResNet-32* with a standard image recognition dataset *Cifar-10* using a single GPU training as the baseline. We observe up to 7.7X training speedup within the cost budget with a slight accuracy decrease—an artifact of asynchronous training but not caused by the use of transient servers. In fact, we observe that model accuracy on average is higher when workers are revoked compared to distributed training without revocation. Our observations in turn ~~suggests~~ suggest that deep learning frameworks could better trade-offs all three performance metrics, i.e., model training time, training cost and accuracy if cloud providers rework the revocation mechanism. In addition, our analysis reveals the inefficiency of current training frameworks in utilizing transient servers, manifesting in the basic support for model checkpointing, dynamic scale up or down training cluster.

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