Speeding up Deep Learning with Transient Servers

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

***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.

***Keywords*-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 [1].

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.

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 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 framework 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

		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 results in a 3.72X speedup with 62.9% monetary savings, compared to running on one K80 on-demand GPU server. In addition, we observe a 1.2% drop in accuracy 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, produces 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.*

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:

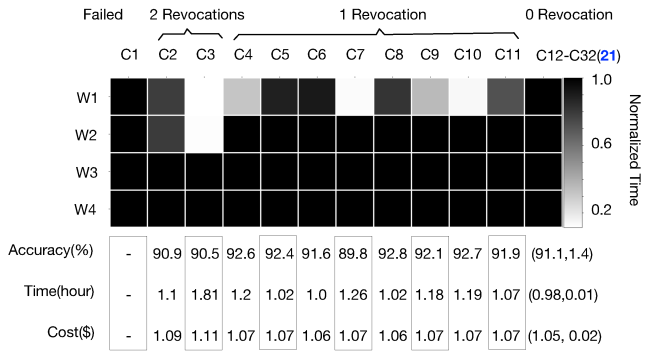
- We compare the training time and cost of distributed training using transient servers to on-demand servers. We observe up to 7.7X training speedup and up to 62.9% monetary savings in our experiments when compared to the single GPU baseline.
- We quantify the revocation impacts of transient servers 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 additional opportunities for mitigating revocation impacts, such as the need for cloud providers 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 the necessary background on distributed training and motivate our selection of parameter server-based asynchronous training (Section II-A). We then explain the opportunities and challenges presented by training with transient servers (Section II-B). An overview of transient-based distributed training is illustrated in Figure 2.

A. Distributed Deep Learning

In this paper, we focus on evaluating distributed training with parameter server-based asynchronous training due to its



	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12-C32(21)
Accuracy(%)	-	90.9	90.5	92.6	92.4	91.6	89.8	92.8	92.1	92.7	91.9	(91.1,1.4)
Time(hour)	-	1.1	1.81	1.2	1.02	1.0	1.26	1.02	1.18	1.19	1.07	(0.98,0.01)
Cost($)	-	1.09	1.11	1.07	1.07	1.06	1.07	1.06	1.07	1.07	1.07	(1.05, 0.02)

Figure 1: ***Quantifying distributed training performance using transient servers.*** *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 ($W1$ to $W4$) and one parameter server. We observed that 21 out of 32 transient clusters completed training with 0 revocations, 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 resulted in a 3.72X speedup and 62.9% monetary savings, compared to running on one `K80` on-demand GPU server.*

popularity and potential resilience to training server failures. The concept of distributed deep learning on multiple GPU servers is relatively new [2], and a number of frameworks such as TensorFlow [3] and FireCaffe [4] have started to support training DNN models using clusters of GPU servers. Note that this approach is different from training on a 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 [5]. 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. 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, 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 [6], [7] that is in charge of updating model parameters (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 of the training process [8] 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 in a process called *model checkpointing*. 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*, respectively. Unlike traditional *on-demand* servers, cloud providers can revoke transient servers at any time [9], [10]. 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 that may evolve over time. For instance, in the case of dynamic pricing, cloud customers may want to regularly monitor prices and adjust the number and type of servers to maximize training performance and reduce costs.

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

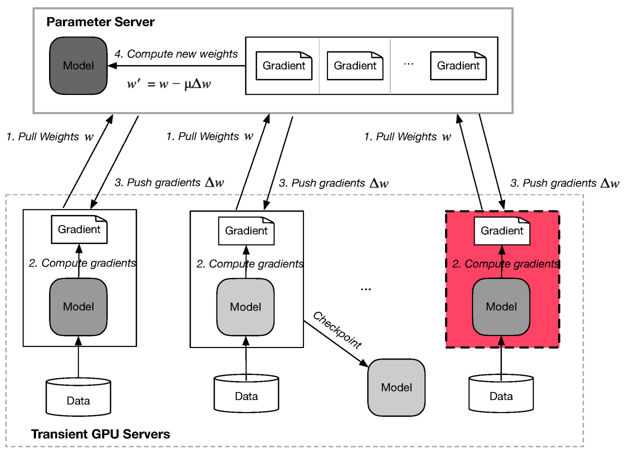


Figure 2: ***Illustration of distributed training on transient GPU servers.*** *We adopt an asynchronous distributed training architecture. The parameter server runs on an on-demand CPU server and the workers (including a special master that is in charge of model checkpointing) run on transient GPU servers.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

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 [11]. 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

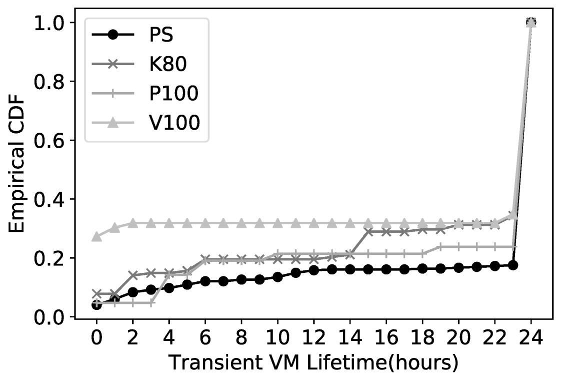


Figure 3: ***CDF of Google preemptible GPU server lifetimes.*** *We measure the lifetime as the time between when a preemptible GPU server is ready to use and when the server is revoked by the Google cloud platform. Note that Google transient servers have a maximum lifetime of 24 hours. We observe that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

were requested at different times, from different data center locations, and with different levels of resource utilization. In Figure 3, we compare the lifetimes of GCE transient servers. We observe that different GPU servers have different revocation patterns. Further we find that even though approximately 70% of servers live the full 24 hours, about 20% are revoked within the first two hours—in the latter case, distributed training that lasts more than two hours will be subject to revocation impacts.

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 answers 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 the revocation of transient servers impact distributed training? (4) What are the benefits and challenges associated with dynamic clusters? (5) What is the performance impact of using heterogeneous server resources?

A. Experimental Setup

Public Cloud Infrastructure: We conducted our experiments using Google Compute Engine (GCE) and the server configurations are shown in Table II. We choose three

GCE instance	Mem. (GB)	vCPU	On-demand ($/hr)	Transient ($/hr)	Savings 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.*

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 *savings potential* column 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. Recall that Google Compute Engine uses a static pricing model.

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 run using an on-demand instance. The reason we use an on-demand instance for the parameter server for distributed training is to avoid the checkpoint restarts that would result if parameter server was revoked. However, we do use transient parameter servers when measuring the lifetime of transient CPU server.

Deep Learning Framework: We leveraged the popular deep learning framework TensorFlow [3] for all our experiments given the relative maturity of the project and support for distributed training. We also used the Tensor2tensor library [12] to assist in the training process. For the model, we selected *ResNet-32* [13], 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* [14], 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.

Performance Metrics: We focus on the performance metrics 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 server lifetimes. For transient servers that were revoked by GCE, their recorded lifetime will typically be shorter than the total training time for the cluster. 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, cost, and accuracy. Training time is defined as the amount of time required to complete the specified training workload. When training the *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 accuracy of the model at *64K* steps as the *converged accuracy*.

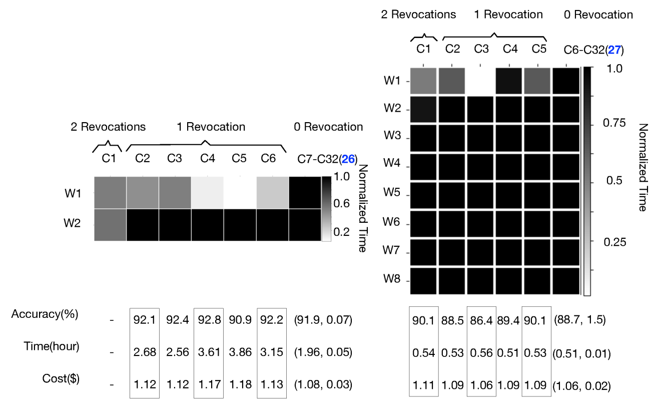
Training cost is calculated using the sum of all cloud servers that participate in the training process. In the case of distributed training, these include GPU servers that are responsible for calculating the gradients and the CPU server that is in charge of updating the model parameters. We calculate 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 [15]. 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 *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 (also 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% savings 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*.



		C1	C2	C3	C4	C5	C6	C7-C32(26)
Accuracy(%)	-	92.1	92.4	92.8	90.9	92.2	(91.9, 0.07)	
Time(hour)	-	2.68	2.56	3.61	3.86	3.15	(1.96, 0.05)	
Cost($)	-	1.12	1.12	1.17	1.18	1.13	(1.08, 0.03)	

	C1	C2	C3	C4	C5	C6-C32(27)
Accuracy(%)	90.1	88.5	86.4	89.4	90.1	(88.7, 1.5)
Time(hour)	0.54	0.53	0.56	0.51	0.53	(0.51, 0.01)
Cost($)	1.11	1.09	1.06	1.09	1.09	(1.06, 0.02)

Figure 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.*

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.

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 failure probability, the larger the cluster size, the lower the impact of revocations. This is because training can still progress in larger clusters, albeit at a degraded performance compared to the initial cluster.*

Summary: Distributed training with transient servers can speed up deep learning by up to 3.72X with 62% cost savings, when compared to training using on-demand servers. Our analysis motivates the need for redesigning distributed training frameworks to support robust model checkpointing and suggests that training with larger cluster sizes allows for 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* by using more powerful GPU servers or *scaling out* by using a cluster of GPU servers. Intuitively, we are asking the question: what is the best cluster configuration given a fixed 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 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 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 accuracy decrease is non-linear as the cluster increases. We observed 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,

		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.*

i.e., prolonging training does not improve accuracy. These observations are consistent with previously noted impacts of stale model parameters on the converged accuracy [6], [16]–[18].

Summary: When configuring the transient server clusters, one needs to consider various factors, including revocation probability, training time reduction, 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.

When we also consider the lifetime of revoked GPU servers (Figure 1 and Figure 4) it appears that 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 (though 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 worst-case scenario. This implies that larger transient clusters are 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 an underperforming GPU server, i.e., a 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 choice of *which* servers to be revoked to the cloud customer, it will enable more flexibility when making tradeoffs between accuracy and training performance.

On the other hand, as the number of revocations 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 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 measurements demonstrate that scaling up with on-demand servers incurs almost 2X higher training costs with almost identical training time and accuracy. This again showcases the 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 potential 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 training and ensure they always have the best cluster configuration given their budget and changing server prices. We refer to this concept as *dynamic transient clusters*.

		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 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.*

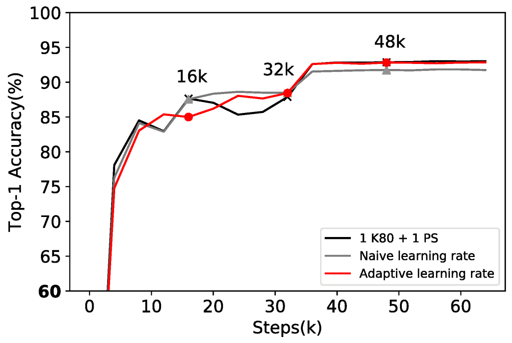
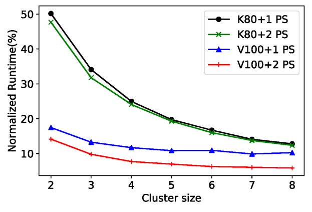


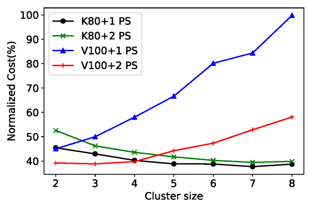
Figure 5: ***Benefits of dynamic transient distributed training and adaptive learning rate.*** *Dynamically scaling training cluster allows training to be finished 40.8% faster than a static cluster. By adaptively setting the learning rate, we mitigate the accuracy degradation caused by naively using sparse mapping.*

As existing distributed training frameworks do not natively support dynamic clusters, we instead propose a technique called *sparse mapping* to enable dynamically adjusting training cluster configurations during runtime. When using sparse mapping, cloud customers specify the maximum number of workers (i.e. GPU servers), also 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 a dynamic cluster also leads to 21.5% cost savings when compared to training with the



(a) *Training time.*



(b) *Training cost.*

Figure 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.*

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 number of *active* workers. We refer to the method of leveraging sparse mapping without changing learning rate as using a *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. In Figure 5, we compare the top-1 accuracy 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 an 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 we empirically demonstrated previously, different classes of transient servers exhibit different revocation probabilities, cost savings, availability, and speed trade-offs. Naturally, this suggests the need to support a mix of servers to balance such trade-offs in distributed training. We refer to such clusters as *heterogeneous* and in this section, we study two types of heterogeneity: the first leverages differences in hardware and the second uses differences in location.

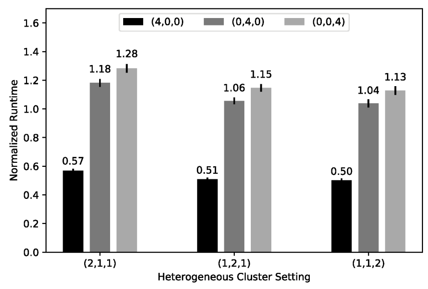
For both types of heterogeneity, we use a fixed cluster size of four transient workers plus an on-demand parameter server. We use this cluster size for two reasons. First, when scaling out with more powerful `V100`, we have observed that training time quickly plateaus after using more than four servers (Figure 6a). That is, the training bottleneck has shifted from the ability to parallelize the gradient computations to how fast the single parameter server can handle the weight pulling and gradient pushing from GPU servers. When using *two* parameter servers 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.

To understand the impact of hardware heterogeneity, we compared three baseline training scenarios using *homogeneous* clusters to the training performance of a variety of *heterogeneous* cluster configurations. Homogeneous clusters consist entirely of servers with the same GPU type while heterogeneous clusters feature a mixture of `K80`, `P100`, and `V100` servers. We denote the configuration of each cluster using the tuple $(N_{K80}, N_{P100}, N_{V100})$ where each value represents the number of GPU servers of that particular type in the cluster. For example, we use the cluster configuration (2, 1, 1) to represent clusters with two `K80` servers and one `P100` and one `V100`. For all of the clusters, we set the total number of GPU servers to be four, i.e., $N_{K80} + N_{P100} + N_{V100} = 4$. In Figure 7, we compare the training performance of three different heterogeneous configurations with that of three homogeneous configurations.

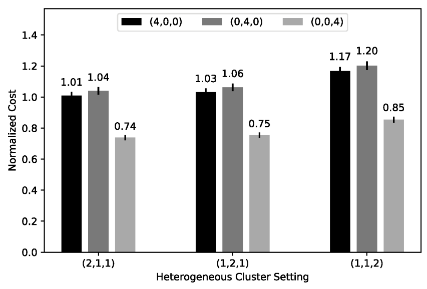
When swapping out two (or three) `K80` machines for more powerful GPU servers, we observe up to a 50% speedup when compared to the homogeneous cluster of four `K80` servers. The heterogeneous configuration (1, 1, 2) with `V100` incurs 17% more monetary cost. Similarly, when swapping out two (or three) `V100` for less powerful GPU servers, we observe up to a 28% slowdown when compared to the homogeneous cluster of four `V100` servers. The heterogeneous configuration (2, 1, 1) with two `K80` reduces the monetary cost by 26%. Our evaluation suggests that mixing in more powerful transient GPU servers significantly increases training speed with a manageable cost increase and negligible accuracy impact.

For understanding the implications of location heterogeneity, we compare the training performance of using clusters where all the workers reside in a single geographic region to clusters with workers split across multiple regions. We choose three US-based regions for our experiments: *us-east1*, *us-central1* and *us-west1*. We represent each cluster configuration using the tuple $(N_{east}, N_{central}, N_{west})$ where each value represents the number of servers running in each region. We place the parameter server in the data center with the largest number of workers for any given cluster.

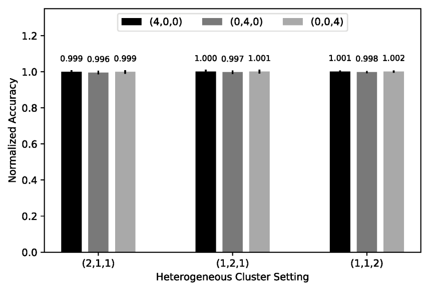
As shown in Figure 8, splitting servers across different regions leads to significant slowdowns, up to 48%. This



(a) Training time.

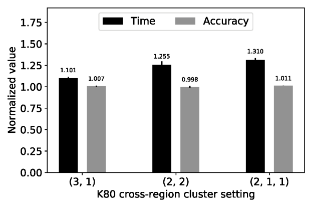


(b) Training cost.

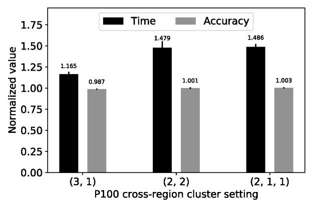


(c) Training accuracy.

*Figure 7: **Training with heterogeneous server hardware.** Mixing workers with less powerful GPUs slows down training by up to 28% but leads to 26% cost savings when compared to training with homogeneous servers. Further, the change in accuracy is negligible.*



(a) K80 clusters.



(b) P100 clusters.

*Figure 8: **Training with heterogeneous server locations.** Using servers from different data centers resulted in a 48% slow down when compared to training within the same region. Interesting, splitting servers across three data centers showed similar performance to splitting across just two regions.*

is because a subset of the workers have to communicate with a parameter server that resides in a different data center. Even though our clusters use an asynchronous training architecture—where workers do not need to wait for each other to receive the updated model parameters—the separated workers contribute *less* work towards completing the specified *64K* steps, slowing down the overall training. We do not observe any additional slow down when splitting clusters across two regions versus all three regions. Interestingly, there is a slight increase in accuracy as the training speed slows, suggesting the potential to mitigate the impact of cross-region training when transient costs are low enough.

Summary: Training with heterogeneous clusters, either in terms hardware or location, results in non-trivial tradeoffs in training cost, accuracy and time. For example, it is more effective to train with heterogeneous hardware clusters in the same data center as the training slow down is roughly proportional to the cost reduction; the saved money can be used to increase cluster size, speeding up training and mitigating revocation impacts. Further, training across geographically-diverse data centers incurs significant overhead due to network communication. Our observations motivate the need to optimize the network communication of distributed training frameworks to take advantage of heterogeneous location clusters.

IV. Related Work

Deep learning frameworks. There are a number of deep learning frameworks [3], [12], [19], [20] 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 [3], we believe the results can be extended to other frameworks, such as Caffe/FireCaffe, CNTK, MXNet [19], [21], [22]. The reason is that current deep learning frameworks share the same distributed training method, adopt a parameter server to maintain training parameters, use SGD-based methods for optimizing model parameters [18], [23], and support distributed training on multi-GPU servers. However, most current deep learning frameworks do not natively support dynamically adding or removing servers while the training process is ongoing. Very recently, MXNet has embarked the efforts to dynamically scale training jobs on EC2 [24]. 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 [25] have compared and studied deep learning performance under different hardware and software configurations. In particular, researchers have investigated the scaling potential of using CPU servers [2], single GPU servers, and multi-GPU servers [26]. As the computational needs of deep learning grows so does the support for distributed training over a cluster of GPU servers [4], [7], [27]. Prior work has considered the impact of network communication [28]–[30]; how to tune hyperparamters, e.g., learning rate and batch size [1], [18], [31]–[33]; and how to mitigate the communication bottlenecks and the impact of stale model parameters [6], [16]–[18]. However, most works on distributed training performance [26], [34], [35] make the implicit assumptions of *static* and *homogenous* cluster configurations. Our study aims to understand the training performance of cheap transient servers that have dynamic availability, revocation patterns, and unit costs. In addition, these previous studies often focus on measuring training speed using the average time to process one mini-batch [25], [26], [36]. While in this work, we consider multiple important performance metrics—including training time, cost, and accuracy—that could be impacted by training on transient servers.

Performance optimization based on transient servers. Since transient servers are cheaper than their on-demand counterparts, many researchers have studied how to effectively run applications on cloud transient servers with as few modifications as possible [37], [38]. Some researchers have proposed transient-aware resource managers [39], [40] to optimize job schedulers by taking into account the revocation rates of transient servers. Other researchers have proposed system-level fault-tolerance techniques such as dynamic checkpointing to optimize the execution time of various applications, including web services [38], [41], big data applications [42]–[45] and other memory-intensive applications [46]. DeepSpotCloud [47] looked at how to effectively train deep learning models by migrating from one GPU server to a cheaper transient server. Our efforts differs from prior work in two major ways. First, we focus on understanding how distributed training can benefit from cheap transient servers. Unlike the 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 explored the feasibility and quantified 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. Conclusions and Future Work

In this paper, we described the first large-scale empirical evaluation of distributed training using transient servers. We compared various transient server cluster configurations for training a popular CNN model called *ResNet-32* with a standard image recognition dataset *Cifar-10*. Using training on a single GPU server as a baseline, we observe up to a 7.7X training speedup within the same cost budget and with a slight accuracy decrease—an artifact of asynchronous training that is not caused by the use of transient servers. In fact, we observe that model accuracy on average is higher when workers are revoked when compared to distributed training without revocation. Our observations suggest that deep learning frameworks could better leverage trade-offs across 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 several ways that current training frameworks can better utilize transient servers, e.g., by offering increased flexibility for model checkpointing and supporting dynamic scaling.

Acknowledgment

We thank all our anonymous reviewers for their insightful comments. This work is supported in part by National Science Foundation grants #1755659 and #1815619, Google Cloud Platform Research credits, the National Natural Science Foundation of China (61802377), and the Youth Innovation Promotion Association at CAS.

References

[1] P. Goyal, P. Dollár, R. Girshick, P. Noordhuis, L. Wesolowski, A. Kyrola, A. Tulloch, Y. Jia, and K. He, "Accurate, large minibatch sgd: Training imagenet in 1 hour," *arXiv preprint arXiv:1706.02677*, 2017.

[2] J. Dean, G. Corrado, R. Monga, K. Chen, M. Devin, M. Mao, A. Senior, P. Tucker, K. Yang, Q. V. Le *et al.*, "Large scale distributed deep networks," in *Advances in neural information processing systems*, 2012.

[3] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean *et al.*, "Tensorflow: A system for large-scale machine learning," in *USENIX Symposium on Operating Systems Design and Implementation*, 2016.

[4] F. N. Iandola, M. W. Moskewicz, K. Ashraf, and K. Keutzer, "Firecaffe: Near-linear acceleration of deep neural network training on compute clusters," in *The IEEE Conference on Computer Vision and Pattern Recognition*, 2016.

[5] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, 2010.

[6] Q. Ho, J. Cipar, H. Cui, S. Lee, J. K. Kim, P. B. Gibbons, G. A. Gibson, G. Ganger, and E. P. Xing, "More effective distributed ml via a stale synchronous parallel parameter server," in *Advances in neural information processing systems*, 2013.

[7] H. Cui, H. Zhang, G. R. Ganger, P. B. Gibbons, and E. P. Xing, "Geeps: Scalable deep learning on distributed gpus with a gpu-specialized parameter server," in *Proceedings of the Eleventh European Conference on Computer Systems*, 2016.

[8] V. Sze, Y. Chen, T. Yang, and J. S. Emer, "Efficient processing of deep neural networks: A tutorial and survey," *Proceedings of the IEEE*, 2017.

[9] Amazon, "Amazon ec2 spot instances," [accessed February 2019]. [Online]. Available: https://aws.amazon.com/ec2/spot/

[10] Google, "Preemptible vm instances," [accessed February 2019]. [Online]. Available: https://cloud.google.com/compute/docs/instances/preemptible

[11] X. Ouyang, D. Irwin, and P. Shenoy, "Spotlight: An information service for the cloud," in *2016 IEEE 36th International Conference on Distributed Computing Systems*, June 2016.

[12] A. Vaswani, S. Bengio, E. Brevdo, F. Chollet, A. N. Gomez, S. Gouws, L. Jones, L. Kaiser, N. Kalchbrenner, N. Parmar, R. Sepassi, N. Shazeer, and J. Uszkoreit, "Tensor2tensor for neural machine translation," *CoRR*, vol. abs/1803.07416, 2018.

[13] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *arXiv preprint arXiv:1512.03385*, 2015.

[14] A. Krizhevsky and G. Hinton, "Learning multiple layers of features from tiny images," Citeseer, Tech. Rep., 2009.

[15] Google Cloud Platform, "Extending per second billing in google cloud," [accessed February 2019]. [Online]. Available: https://cloud.google.com/blog/products/gcp/extending-per-second-billing-in-google

[16] W. Zhang, S. Gupta, X. Lian, and J. Liu, "Staleness-aware async-sgd for distributed deep learning," *arXiv preprint arXiv:1511.05950*, 2015.

[17] S. Dutta, G. Joshi, S. Ghosh, P. Dube, and P. Nagpurkar, "Slow and stale gradients can win the race: Error-runtime trade-offs in distributed sgd," *arXiv preprint arXiv:1803.01113*, 2018.

[18] J. Chen, X. Pan, R. Monga, S. Bengio, and R. Jozefowicz, "Revisiting distributed synchronous sgd," *arXiv preprint arXiv:1604.00981*, 2016.

[19] Facebook Research, "Caffe2," [accessed February 2019]. [Online]. Available: https://caffe2.ai

[20] A. Paszke, S. Gross, S. Chintala, and G. Chanan, "Pytorch," [accessed February 2019]. [Online]. Available: https://pytorch.org

[21] Microsoft Research, "Microsoft cognitive toolkit," [accessed February 2019]. [Online]. Available: https://github.com/Microsoft/CNTK

[22] A. Foundation, "Apache mxnet," [accessed February 2019]. [Online]. Available: https://mxnet.incubator.apache.org

[23] S. Zhang, A. E. Choromanska, and Y. LeCun, "Deep learning with elastic averaging sgd," in *Advances in Neural Information Processing Systems 28*, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds. Curran Associates, Inc., 2015.

[24] Amazon Web Services - Labs, "Dynamic training with apache mxnet," [accessed February 2019]. [Online]. Available: https://github.com/awslabs/dynamic-training-with-apache-mxnet-on-aws

[25] S. Shi, Q. Wang, P. Xu, and X. Chu, "Benchmarking state-of-the-art deep learning software tools," in *7th International Conference on Cloud Computing and Big Data*, 2016.

[26] S. Shi, Q. Wang, and X. Chu, "Performance modeling and evaluation of distributed deep learning frameworks on gpus," in *2018 IEEE 16th DASC/PiCom/DataCom/CyberSciTech*, 2018.

[27] T. Chilimbi, Y. Suzue, J. Apacible, and K. Kalyanaraman, "Project adam: Building an efficient and scalable deep learning training system," in *USENIX Symposium on Operating Systems Design and Implementation*, 2014.

[28] Y. Lin, S. Han, H. Mao, Y. Wang, and W. J. Dally, "Deep gradient compression: Reducing the communication bandwidth for distributed training," *arXiv preprint arXiv:1712.01887*, 2017.

[29] W. Wen, C. Xu, F. Yan, C. Wu, Y. Wang, Y. Chen, and H. Li, "Terngrad: Ternary gradients to reduce communication in distributed deep learning," in *Advances in neural information processing systems*, 2017.

[30] N. Strom, "Scalable distributed dnn training using commodity gpu cloud computing," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.

[31] A. Srinivasan, A. Jain, and P. Barekatain, "An analysis of the delayed gradients problem in asynchronous sgd," 2018.

[32] Y. You, Z. Zhang, C.-J. Hsieh, J. Demmel, and K. Keutzer, "Imagenet training in minutes," in *Proceedings of the 47th International Conference on Parallel Processing*, 2018.

[33] T. Akiba, S. Suzuki, and K. Fukuda, "Extremely large minibatch sgd: Training resnet-50 on imagenet in 15 minutes," *arXiv preprint arXiv:1711.04325*, 2017.

[34] F. Yan, O. Ruwase, Y. He, and T. Chilimbi, "Performance modeling and scalability optimization of distributed deep learning systems," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2015.

[35] T. Ben-Nun and T. Hoefler, "Demystifying parallel and distributed deep learning: An in-depth concurrency analysis," *CoRR*, vol. abs/1802.09941, 2018.

[36] Y. Peng, Y. Bao, Y. Chen, C. Wu, and C. Guo, "Optimus: an efficient dynamic resource scheduler for deep learning clusters," in *Proceedings of the Thirteenth EuroSys Conference*, 2018.

[37] S. Shastri and D. Irwin, "Hotspot: Automated server hopping in cloud spot markets," in *Proceedings of the Symposium on Cloud Computing*, 2017.

[38] P. Sharma, S. Lee, T. Guo, D. Irwin, and P. Shenoy, "Spotcheck: Designing a derivative iaas cloud on the spot market," in *Proceedings of the Tenth European Conference on Computer Systems*, 2015.

[39] P. Sharma, D. Irwin, and P. Shenoy, "Portfolio-driven resource management for transient cloud servers," *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, 2017.

[40] A. Harlap, A. Tumanov, A. Chung, G. R. Ganger, and P. B. Gibbons, "Proteus: agile ml elasticity through tiered reliability in dynamic resource markets," in *Proceedings of the Twelfth European Conference on Computer Systems*, 2017.

[41] A. Harlap, A. Chung, A. Tumanov, G. R. Ganger, and P. B. Gibbons, "Tributary: spot-dancing for elastic services with latency slos," in *USENIX Annual Technical Conference*, 2018.

[42] N. Chohan, C. Castillo, M. Spreitzer, M. Steinder, A. N. Tantawi, and C. Krintz, "See spot run: Using spot instances for mapreduce workflows." *HotCloud*, vol. 10, 2010.

[43] P. Sharma, T. Guo, X. He, D. Irwin, and P. Shenoy, "Flint: batch-interactive data-intensive processing on transient servers," in *Proceedings of the Eleventh European Conference on Computer Systems*, 2016.

[44] Y. Yan, Y. Gao, Y. Chen, Z. Guo, B. Chen, and T. Moscibroda, "Tr-spark: Transient computing for big data analytics," in *Proceedings of the Seventh ACM Symposium on Cloud Computing*, 2016.

[45] S. Subramanya, T. Guo, P. Sharma, D. Irwin, and P. Shenoy, "Spoton: a batch computing service for the spot market," in *Proceedings of the sixth ACM symposium on cloud computing*, 2015.

[46] C. Wang, B. Urgaonkar, A. Gupta, G. Kesidis, and Q. Liang, "Exploiting spot and burstable instances for improving the cost-efficacy of in-memory caches on the public cloud," in *Proceedings of the Twelfth European Conference on Computer Systems*, 2017.

[47] K. Lee and M. Son, "Deepspotcloud: leveraging cross-region gpu spot instances for deep learning," in *IEEE 10th International Conference on Cloud Computing*, 2017.