The Non-IID Data Quagmire of Decentralized Machine Learning

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Abstract

Many large-scale machine learning (ML) applications need to perform *decentralized* learning over datasets generated at different devices and locations. Such datasets pose a significant challenge to decentralized learning because their different contexts result in significant data distribution skew across devices/locations. In this paper, we take a step toward better understanding this challenge by presenting a detailed experimental study of decentralized DNN training on a common type of data skew: skewed distribution of data labels across devices/locations. Our study shows that: (i) skewed data labels are a fundamental and pervasive problem for decentralized learning, causing significant accuracy loss across many ML applications, DNN models, training datasets, and decentralized learning algorithms; (ii) the problem is particularly challenging for DNN models with batch normalization; and (iii) the degree of data skew is a key determinant of the difficulty of the problem. Based on these findings, we present SkewScout, a system-level approach that adapts the communication frequency of decentralized learning algorithms to the (skew-induced) accuracy loss between data partitions. We also show that group normalization can recover much of the accuracy loss of batch normalization.

1. Introduction

The advancement of machine learning (ML) is heavily dependent on the processing of massive amounts of data. The most timely and relevant data are often generated at different devices all over the world, e.g., data collected by mobile phones and video cameras. Because of communication and privacy constraints, gathering all such data for centralized processing can be impractical/infeasible. For example, moving raw data across national borders is subject to data sovereignty law constraints (e.g., GDPR (European Parliament, 2016)). Similar constraints apply to centralizing private data from phones.

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These constraints motivate the need for ML training over widely distributed data (***decentralized learning***). For example, *geo-distributed learning* (Hsieh et al., 2017) trains a global ML model over data spread across geo-distributed data centers. Similarly, *federated learning* (McMahan et al., 2017) trains a centralized model over data from a large number of mobile devices. Federated learning has been an important topic both in academia (140+ papers in 2019) and industry (500+ million installations on Android devices).

Key Challenges in Decentralized Learning. There are two key challenges in decentralized learning. First, training a model over decentralized data using traditional training approaches (i.e., those designed for centralized data, often using a bulk synchronous parallel (BSP) approach (Valiant, 1990)) requires massive amounts of communication. Doing so drastically slows down the training process because the communication is bottlenecked by the limited wide-area or mobile network bandwidth (Hsieh et al., 2017; McMahan et al., 2017). Second, decentralized data is typically generated at different contexts, which can lead to significant differences in the *distribution* of data across data partitions. For example, facial images collected by cameras would reflect the demographics of each camera's location, and images of kangaroos can be collected only from cameras in Australia or zoos. Unfortunately, existing decentralized learning algorithms (e.g., (Hsieh et al., 2017; McMahan et al., 2017; Smith et al., 2017; Lin et al., 2018; Tang et al., 2018)) mostly focus on reducing communication, as they either (i) assume the data partitions are independent and identically distributed (IID) or (ii) conduct only very limited studies on non-IID data partitions. This leaves a key question mostly unanswered: *What happens to ML applications and decentralized learning algorithms when their data partitions are not IID?*

Our Goal and Key Findings. We aim to take a step to further the understanding of the above key question. In this work, we focus on a common type of non-IID data, widely used in prior work (e.g., (McMahan et al., 2017; Tang et al., 2018; Zhao et al., 2018)): skewed distribution of data labels across devices/locations. Such *skewed label partitions* arise frequently in the real world (see §2.2 for examples). Our study covers various DNN applications, DNNs, training datasets, decentralized learning algorithms, and degrees of label skew. Our study reveals three key findings:

- Training over skewed label partitions is a fundamental and pervasive problem for decentralized learning. Three decentralized learning algorithms (Hsieh et al., 2017; McMahan et al., 2017; Lin et al., 2018) suffer from major model quality loss when run to convergence on skewed label partitions, across the applications, models, and training datasets in our study.
- DNNs with *batch normalization* (Ioffe & Szegedy, 2015) are particularly vulnerable to skewed label partitions, suffering significant model quality loss even under BSP, the most communication-heavy approach.
- The degree of skew is a key determinant of the difficulty level of the problem.

These findings reveal that non-IID data is an important yet heavily understudied challenge in decentralized learning, worthy of extensive study. To facilitate further study on skewed label partitions, we release a real-world, geo-tagged dataset of common mammals on Flickr (Flickr), which is openly available at https://doi.org/10.5281/zenodo.3676081 (§2.2).

Solutions. As two initial steps towards addressing the vast challenge of non-IID data, we first show that among the many proposed alternatives to batch normalization, *group normalization* (Wu & He, 2018) avoids the skew-induced accuracy loss of batch normalization under BSP. With this fix, all models in our study achieve high accuracy on skewed label partitions under (communication-heavy) BSP, and the problem can be viewed as a trade-off between accuracy and the amount of communication. Intuitively, there is a tug-of-war among different data partitions, with each partition pulling the model to reflect its data, and only close communication, tuned to the skew-induced accuracy loss, can save the overall model accuracy of the algorithms in our study. Accordingly, we present SkewScout, which periodically sends local models to remote data partitions and compares the model performance (e.g., validation accuracy) between local and remote partitions. Based on the accuracy loss, SkewScout adjusts the amount of communication among data partitions by controlling how *relaxed* the decentralized learning algorithms should be, such as controlling the threshold that determines which parameters are worthy of communication. Thus, SkewScout can seamlessly integrate with decentralized learning algorithms that provide such communication control. Our experimental results show that SkewScout's adaptive approach automatically reduces communication by 9.6× (under high skew) to 34.1× (under mild skew) while retaining the accuracy of BSP.

Contributions. We make the following contributions. First, we conduct a detailed empirical study on the problem of skewed label partitions. We show that this problem is a fundamental and pervasive challenge for decentralized learning. Second, we build and release a large real-world dataset to facilitate future study on this challenge. Third, we make a new observation showing that this challenge is particularly problematic for DNNs with batch normalization, even under BSP. We discuss the root cause of this problem and we find that it can be addressed by using an alternative normalization technique. Fourth, we show that the difficulty level of this problem varies with the data skew. Finally, we design and evaluate SkewScout, a system-level approach that adapts the communication frequency among data partitions to reflect the skewness in the data, seeking to maximize communication savings while preserving model accuracy.

2. Background and Motivation

We first provide background on popular decentralized learning algorithms (§2.1). We then highlight a real-world example of skewed label partitions: geographical distribution of mammal pictures on Flickr, among other examples (§2.2).

2.1. Decentralized Learning

In a decentralized learning setting, we aim to train an ML model w based on all the training data samples (x_i, y_i) that are generated and stored in one of the K partitions (denoted as P_k). The goal of the training is to fit w to all data samples. Typically, most decentralized learning algorithms assume the data samples are independent and identically distributed (IID) among different P_k, and we refer to such a setting as the *IID setting*. Conversely, we call it the *Non-IID setting* if such an assumption does not hold.

We evaluate three popular decentralized learning algorithms to see how they perform on different applications over the IID and Non-IID settings, using skewed label partitions. These algorithms can be used with a variety of stochastic gradient descent (SGD) (Robbins & Monro, 1951) approaches, and aim to reduce communication, either among data partitions (P_k) or between the data partitions and a centralized server.

- `Gaia` (Hsieh et al., 2017), a geo-distributed learning algorithm that dynamically eliminates insignificant communication among data partitions. Each partition P_k accumulates updates Δw_j to each model weight w_j locally, and communicates Δw_j to all other data partitions only when its relative magnitude exceeds a predefined threshold (Algorithm 1 in Appendix A[1]).
- `FederatedAveraging` (McMahan et al., 2017), a popular algorithm for federated learning that combines local SGD on each client with model averaging. The algorithm selects a subset of the partitions P_k in each epoch, runs a pre-specified number of local SGD steps on each selected P_k, and communicates the resulting models back to a centralized server. The server averages all these models and uses the averaged w as the starting

[1] All Appendices are in the supplemental material.

point for the next epoch. (Algorithm 2 in Appendix A).

- `DeepGradientCompression` (Lin et al., 2018), a popular algorithm that communicates only a pre-specified amount of gradients each training step, with various techniques to retain model quality such as momentum correction, gradient clipping (Pascanu et al., 2013), momentum factor masking, and warm-up training (Goyal et al., 2017) (Algorithm 3 in Appendix A).

In addition to these decentralized learning algorithms, we show the results of using BSP (Valiant, 1990) over the IID and Non-IID settings. BSP is significantly slower than the above algorithms because it does not seek to reduce communication: all updates from each P_k are shared among all data partitions after each training step. As noted earlier, for decentralized learning, there is a natural tension between the amount of communication and the quality of the resulting model. Different data distributions among the P_k pull the model in different directions—more communication helps mitigate this "tug-of-war" so that the model well-represents all the data. Thus, BSP, with its full communication at every step, is used to establish a quality target for trained models.

2.2. Real-World Examples of Skewed Label Partitions

Non-IID data among devices/locations encompass many different forms. There can be skewed distribution of features (probability $\mathcal{P}(x)$), labels (probability $\mathcal{P}(y)$), or the relationship between features and labels (e.g., varying $\mathcal{P}(y|x)$ or $\mathcal{P}(x|y)$) among devices/locations (Kairouz et al., 2019) (see more discussion in Appendix K). In this work, we focus on skewed distribution of labels ($\mathcal{P}_{P_i}(y) \nsim \mathcal{P}_{P_j}(y)$ for different data partitions P_i and P_j), which is also the setting considered by most prior work in this domain (e.g., (McMahan et al., 2017; Tang et al., 2018; Zhao et al., 2018)).

Skewed distribution of labels is common whenever data are generated from heterogeneous users or locations. For example, pedestrians and bicycles are more common in street cameras than in highway cameras (Luo et al., 2019). In facial recognition tasks, most individuals appear in only a few locations around the world. Certain types of clothing (mittens, cowboy boots, kimonos, etc.) are nearly non-existent in many parts of the world. Similarly, certain mammals (e.g., kangaroos) are far more likely to show up in certain locations (Australia). In the rest of this section, we highlight this phenomenon with a study of the geographical distribution of mammal pictures on Flickr (Flickr).

Dataset Creation. We start with the 48 classes in the *mammal* subcategory of the 600 most common classes for bounding boxes in Open Images V4 (Kuznetsova et al., 2018). For each class label, we use Flickr's API to search for relevant pictures. Due to noise in Flickr search results (e.g., "jaguar" returns the mammal or the car), we clean the data with a state-of-the-art DNN, PNAS (Liu et al., 2018), which is pre-trained on ImageNet. As we can only clean classes that exist in both Open Images and ImageNet, we end up with 41 mammal classes and 736,005 total pictures. We call the resulting dataset the *Flickr-Mammal* dataset (see Appendix B for more details).

Geographical Analysis. We map each Flickr picture's geotag to its corresponding geographic regions based on the M49 Standard (United Nation Statistics Division, 2019). As we are mostly interested in the distribution of labels ($\mathcal{P}(y)$) among different regions, we normalize the number of samples across region (non-normalized results are similar (Appendix B)). Table 1 illustrates the top-5 classes among first-level regions (continents) and their normalized share of samples in the world.

Region	Top 1	Top 2	Top 3	Top 4	Top 5
Africa	zebra (72%)	antelope (71%)	lion (68%)	cheetah (62%)	hippopotamus (59%)
Americas	mule (84%)	skunk (82%)	armadillo (73%)	harbor seal (65%)	squirrel (61%)
Asia	panda (64%)	hamster (59%)	monkey (58%)	camel (51%)	red panda (42%)
Europe	lynx (72%)	hedgehog (56%)	sheep (56%)	deer (43%)	otter (43%)
Oceania	kangaroo (92%)	koala (92%)	whale (44%)	sea lion (34%)	alpaca (32%)

Table 1. Top-5 mammals in each continent and their share of samples worldwide (e.g., 72% of zebra images are from Africa).

Skewed distribution of labels is a natural phenomenon. As Table 1 shows, the top-5 mammals in each continent constitute 32%–92% of the normalized sample share in the world (compared to 20% if the distribution were IID). As expected, the top mammals in each region reflect their population share in the world (e.g., kangaroos/koalas in Oceania and zebras/antelopes in Africa). Furthermore, there is *no overlap* for the top-5 classes among different continents, which suggests drastically different label distributions ($\mathcal{P}(y)$) among continents. We observe a similar phenomenon when the analysis is done based on second-level geographical regions (Appendix B). Our observations show that in a decentralized learning setting, where such images would be collected and stored in their native regions, the distribution of labels across partitions would be highly skewed.

3. Experimental Setup

Our study consists of three dimensions: *(i)* ML applications/models, *(ii)* decentralized learning algorithms, and *(iii)* degree of data skew. We explore all three dimensions with rigorous experimental methodologies. In particular, we make sure the accuracy of our trained ML models on IID data matches the reported accuracy in corresponding papers. All source code and settings are available at https://github.com/kevinhsieh/non_iid_dml.

Applications. We evaluate different deep learning applications, DNN model structures, and training datasets:

- IMAGE CLASSIFICATION with four DNN models: AlexNet (Krizhevsky et al., 2012), GoogLeNet (Szegedy et al., 2015), LeNet (LeCun et al., 1998), and ResNet (He et al., 2016). We use two datasets, CIFAR-10 (Krizhevsky, 2009) and ImageNet (Russakovsky et al., 2015). We use the default validation set of each of the two datasets to quantify the validation accuracy as our model quality metric. We use popular datasets in order to compare model accuracy with existing work, and we also report results with our *Flickr-Mammal* dataset.
- FACE RECOGNITION with the center-loss face model (Wen et al., 2016) over the CASIA-WebFace (Yi et al., 2014) dataset. We use verification accuracy on the LFW dataset (Huang et al., 2007) as our model quality metric.

For all applications, we tune the training parameters (e.g., learning rate, minibatch size, number of epochs, etc.) such that the baseline model (BSP in the IID setting) achieves the model quality of the corresponding original paper. We then use these training parameters in all other settings. We further ensure that training/validation accuracy has stopped improving by the end of all our experiments. Appendix C lists all major training parameters in our study.

Non-IID Data Partitions. In addition to studying *Flickr-Mammal*, we create non-IID data partitions by partitioning datasets using the data labels, i.e., using image classes for image classification and person identities for face recognition. We control the *skewness* by controlling the fraction of data that are non-IID. For example, 20% non-IID indicates 20% of the dataset is partitioned by labels, while the remaining 80% is partitioned uniformly at random. §4 and §5 focus on the 100% non-IID setting in which the entire dataset is partitioned using labels, while §6 studies the effect of varying the skewness. As our goal is to train a global model, the model is tested on the entire validation set.

Hyper-Parameters Selection. The algorithms we study provide the following hyper-parameters (see Appendix A for details of these algorithms) to control the amount of communication (and hence the training time):

- `Gaia` uses T_0, the initial threshold to determine if an update (Δw_j) is significant. The significance threshold decreases whenever the learning rate decreases.
- `FederatedAveraging` uses $Iter_{Local}$ to control the number of local SGD steps on each selected P_k.
- `DeepGradientCompression` uses s to control the sparsity of updates (update magnitudes in top s percentile are exchanged). Following the original paper (Lin et al., 2018), s follows a warm-up schedule: 75%, 93.75%, 98.4375%, 99.6%, 99.9%. We use a hyper-parameter E_{warm}, the number of epochs for each warm-up sparsity, to control the duration of the warm-up. For example, if $E_{warm} = 4$, s is 75% in epochs 1–4, 93.75% in epochs 5–8, and so on.

We select a hyper-parameter θ of each decentralized learning algorithm (T_0, $Iter_{Local}$, E_{warm}) so that *(i)* θ achieves the same model quality as BSP in the IID setting and *(ii)* θ achieves similar communication savings across the three decentralized learning algorithms. We study the sensitivity of our findings to the choice of θ in §4.4.

4. Non-IID Study: Results Overview

This paper seeks to answer the question of what happens to ML applications, ML models, and decentralized learning algorithms when their data label partitions are not IID. In this section, we provide an overview of our findings, showing that skewed label partitions cause *major model quality loss*, across many applications, models, and algorithms.

4.1. Image Classification

We first present the model quality with different decentralized learning algorithms in the IID and Non-IID settings for IMAGE CLASSIFICATION using the CIFAR-10 dataset. We use five partitions ($K = 5$) in this evaluation, and we discuss results with more partitions in Appendix F. As the CIFAR-10 dataset consists of ten object classes, each data partition has two object classes in the Non-IID setting. Figure 1 shows the results with four popular DNNs (AlexNet, GoogLeNet, LeNet, and ResNet). (Convergence curves for AlexNet and ResNet are shown in Appendix D.) According to the hyper-parameter criteria in §3, we select $T_0 = 10\%$ for `Gaia`, $Iter_{Local} = 20$ for `FederatedAveraging`, and $E_{warm} = 8$ for `DeepGradientCompression`. We make two major observations.

1) Non-IID data is a pervasive problem. *All* three decentralized learning algorithms lose significant model quality for *all* four DNNs in the Non-IID setting. We see that while these algorithms retain the validation accuracy of BSP in the *IID setting* with 15×–20× communication savings (agreeing with the results from the original papers for these algorithms), they lose 3% to 74% validation accuracy in the *Non-IID setting*. Simply running these algorithms for more epochs would not help because the training/validation accuracy has already stopped improving. Furthermore, the training completely diverges in some cases, such as `DeepGradientCompression` with GoogLeNet and ResNet20 (`DeepGradientCompression` with ResNet20 also diverges in the IID setting). The pervasiveness of the problem is quite surprising, as we have a diverse set of decentralized learning algorithms and DNNs. This result shows that Non-IID data is a pervasive and challenging problem for decentralized learning, and this problem has been heavily understudied. §4.3 discusses potential causes of this problem.

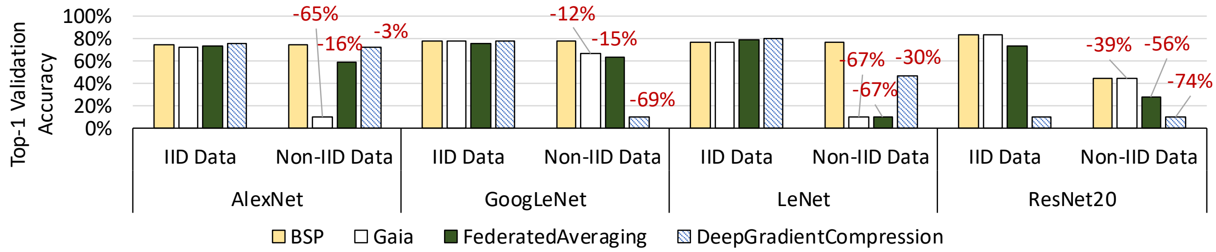


Figure 1. Top-1 validation accuracy for IMAGE CLASSIFICATION over the CIFAR-10 dataset. A "-x%" label above a bar indicates the accuracy loss relative to BSP in the IID setting.

2) Even BSP cannot completely solve this problem. We see that even BSP, with its full communication at every step, cannot retain model quality for some DNNs in the Non-IID setting. The validation accuracy of ResNet20 in the Non-IID setting is 39% lower than that in the IID setting. This finding suggests that, for some DNNs, it *may not be possible* to solve the Non-IID data challenge by increasing communication between data partitions. We find that this problem exists not only in ResNet20, but also in all other DNNs we study with batch normalization (ResNet10, BN-LeNet (Ioffe & Szegedy, 2015) and Inception-v3 (Szegedy et al., 2016)). We discuss this problem and potential solutions in §5.

The same trend in a larger dataset. We conduct a similar study using the ImageNet dataset (Russakovsky et al., 2015) (1,000 image classes). We observe the same problems in the ImageNet dataset (e.g., an 8.1% to 61.7% accuracy loss on ResNet10), whose number of classes is two orders of magnitude more than the CIFAR-10 dataset. Appendix E discusses the experiment in detail.

The same problem in real-world datasets. We run similar experiments on our Flickr-Mammal dataset. We use five partitions (K=5) in this experiment, one for each continent, where each partition has as its local training data precisely the images from its corresponding continent. Thus, we capture the real-world non-IID setting present in Flickr-Mammal. For comparison, we also consider an artificial IID setting, in which all the Flickr-Mammal images are randomly distributed among the five partitions. Figure 2 shows the results. We use GoogLeNet in this experiment, and we select $T_0 = 10\%$ for `Gaia` and $Iter_{Local} = 20$ for `FederatedAveraging` based on the criteria in §3. We observe the same problems for decentralized learning algorithms on this real-world dataset. Specifically, `Gaia` and `FederatedAveraging` are able to retain the model quality in the (artificial) IID setting, but they lose 3.7% and 3.2% accuracy in the (real-world) Non-IID setting, respectively. The loss is smaller compared to Figure 1 in part because most data labels still exist in all data partitions in the (real-world) Non-IID setting, which makes the problem easier than the 100% non-IID setting. This loss arises even with modest hyper-parameter settings, and is expected to be larger with settings that more greatly reduce communication. We also show that the loss increases to 5.2% and

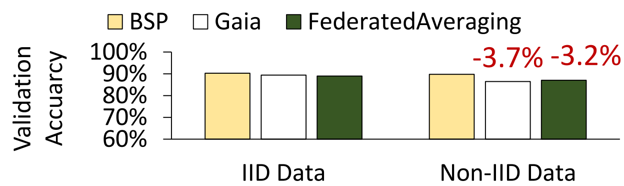


Figure 2. GoogLeNet's Top-1 validation accuracy for IMAGE CLASSIFICATION over the Flickr-Mammal dataset, where 5% data are randomly selected as the validation set. Non-IID Data is based on real-world data distribution among continents, and IID Data is the artificial setting in which images are randomly assigned to partitions. Each "-x%" label indicates the accuracy loss relative to BSP in the IID setting. Note: The y-axis starts at 60% accuracy.

5.5%, respectively, when Flickr-Mammal is partitioned at the subcontinent level (Appendix F). This is significant as the result suggests that skewed labels arising in real-world settings are a major problem for decentralized learning.

4.2. Face Recognition

We further examine another popular ML application, FACE RECOGNITION, to see if the Non-IID data problem is a challenge across different applications. We use two partitions in this evaluation. According to the hyper-parameter criteria in §3, we select T_0=20% for `Gaia` and $Iter_{Local}$=50 for `FederatedAveraging`. It is worth noting that the verification process of FACE RECOGNITION is fundamentally different from IMAGE CLASSIFICATION, as FACE RECOGNITION does *not* use the classification layer (and thus the training labels) at all in the verification process. Instead, for each pair of verification images, the DNN uses the distance between the feature vectors of these images to determine whether the two images are of the same person.

The same problem in different applications. Figure 3 shows the LFW verification accuracy. Again, the same problem happens: the decentralized learning algorithms work

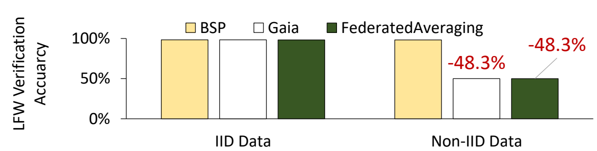


Figure 3. LFW verification accuracy for FACE RECOGNITION. Labels show the accuracy loss relative to BSP in the IID setting.

well in the IID setting, but they lose significant accuracy in the Non-IID setting. In fact, both `Gaia` and `Federated-Averaging` cannot converge to a useful model in the Non-IID setting: their 50% accuracy is no better than random guessing for the binary questions. This result is interesting because the labels of the validation dataset are completely different from the labels of the training dataset, but the validation accuracy is still severely impacted by the non-IID data label partitions in the training set.

4.3. The Problem of Decentralized Algorithms

The above results show that three diverse decentralized learning algorithms all experience drastic accuracy losses in the Non-IID setting. We find two reasons for the accuracy loss. First, for algorithms such as `Gaia` that save communication by allowing small model differences in each partition P_k, the Non-IID setting results in *completely different models among* P_k. The small differences give local models room for specializing to local data. Second, for algorithms that save communication by synchronizing sparsely (e.g., `FederatedAveraging` and `Deep-GradientCompression`), each P_k generates more diverged gradients in the Non-IID setting, which is not surprising as each P_k sees vastly different training data. When they are finally synchronized, they may have diverged so much from the global model that they push the global model the wrong direction. See Appendix G for further details.

4.4. Algorithm Hyper-Parameters

We also study the sensitivity of the Non-IID problem to hyper-parameter choice among decentralized learning algorithms. We find that even relatively conservative hyper-parameter settings, which incur high communication costs, still suffer major accuracy loss in the Non-IID setting. In the IID setting, on the other hand, the *same* hyper-parameter achieves similar high accuracy as BSP. In other words, the the Non-IID problem is not specific to particular hyper-parameter choices. Appendix H shows supporting results.

5. Batch Normalization: Problem and Solution

5.1. Batch Normalization in the Non-IID Setting

How BatchNorm works. Batch normalization (BatchNorm) (Ioffe & Szegedy, 2015) is one of the most popular mechanisms in deep learning (20,000+ citations as of August 2020). BatchNorm aims to stabilize a DNN by normalizing the input distribution to zero mean and unit variance. Because the *global* mean and variance are unattainable with stochastic training, BatchNorm uses *minibatch mean and variance* as an estimate of the global mean and variance. Specifically, for each minibatch $\mathcal{B}$, BatchNorm calculates the minibatch mean $\mu_{\mathcal{B}}$ and variance $\sigma_{\mathcal{B}}$, and then uses $\mu_{\mathcal{B}}$ and $\sigma_{\mathcal{B}}$ to normalize each input in $\mathcal{B}$. BatchNorm enables faster and more stable training because it enables larger learning rates (Bjorck et al., 2018; Santurkar et al., 2018).

BatchNorm and the Non-IID setting. While BatchNorm is effective in practice, its dependence on minibatch mean and variance ($\mu_{\mathcal{B}}$ and $\sigma_{\mathcal{B}}$) is known to be problematic in certain settings. This is because BatchNorm uses $\mu_{\mathcal{B}}$ and $\sigma_{\mathcal{B}}$ for training, but it typically uses an estimated global mean and variance (μ and σ) for validation. If there is a major mismatch between these means and variances, the validation accuracy is going to be low. This can happen if the minibatch size is small or the sampling of minibatches is not IID (Ioffe, 2017). The Non-IID setting in our study exacerbates this problem because each data partition P_k sees very different training samples. Hence, the $\mu_{\mathcal{B}}$ and $\sigma_{\mathcal{B}}$ in each partition can vary significantly across the partitions, and the synchronized global model may not work for *any* set of data. Worse still, we cannot simply increase the minibatch size or do better minibatch sampling to solve this problem, because in the Non-IID setting the underlying dataset in each P_k does not represent the global dataset.

We validate if there is indeed major divergence in $\mu_{\mathcal{B}}$ and $\sigma_{\mathcal{B}}$ among different P_k in the Non-IID setting. We calculate the divergence of $\mu_{\mathcal{B}}$ as the difference between $\mu_{\mathcal{B}}$ in different P_k over the average $\mu_{\mathcal{B}}$ (i.e., it is $\frac{||\mu_{\mathcal{B},P_0} - \mu_{\mathcal{B},P_1}||}{||AVG(\mu_{\mathcal{B},P_0},\, \mu_{\mathcal{B},P_1})||}$ for two partitions P_0 and P_1). We use the average $\mu_{\mathcal{B}}$ over every 100 minibatches in each P_k so that we get better estimation. Figure 4 depicts the divergence of $\mu_{\mathcal{B}}$ for each channel of the first layer of BN-LeNet, which is constructed by inserting BatchNorm to LeNet after each convolutional layer. As we see, the divergence of $\mu_{\mathcal{B}}$ is significantly larger in the Non-IID setting (between 6% to 61%) than in the IID setting (between 1% to 5%). We also observe the same trend in minibatch variances $\sigma_{\mathcal{B}}$ (not shown). As this problem has nothing to do with the amount of communication among P_k, it explains why even BSP cannot retain model accuracy for BatchNorm in the Non-IID setting.

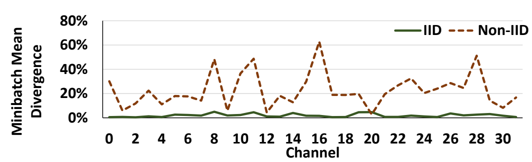


Figure 4. Minibatch mean divergence for the first layer of BN-LeNet over CIFAR-10 using two P_k.

5.2. Alternatives to Batch Normalization

As the problem of BatchNorm in the Non-IID setting is due to its dependence on minibatches, the natural solution is to replace BatchNorm with alternative normalization mechanisms that are *not* dependent on minibatches. Unfortunately, most existing alternative normalization mechanisms (Weight Normalization (Salimans & Kingma, 2016), Layer Normalization (Ba et al., 2016), Batch Renormalization (Ioffe, 2017)) have their own drawbacks (see Appendix I). Here, we discuss a particular mechanism that may be used instead.

Group Normalization. Group Normalization (GroupNorm) (Wu & He, 2018) is an alternative normalization mechanism that aims to overcome the shortcomings of BatchNorm and Layer Normalization (LayerNorm). GroupNorm divides adjacent channels into groups of a prespecified size $\mathcal{G}_{size}$, and computes the per-group mean and variance for *each input sample*. Hence, GroupNorm does not depend on minibatches for normalization (the shortcoming of BatchNorm), and GroupNorm does not assume all channels make equal contributions (the shortcoming of LayerNorm).

We evaluate GroupNorm with BN-LeNet over CIFAR-10. We carefully select $\mathcal{G}_{size} = 2$, which works best with this DNN. Figure 5 shows the Top-1 validation accuracy with GroupNorm and BatchNorm across decentralized learning algorithms. We make two major observations.

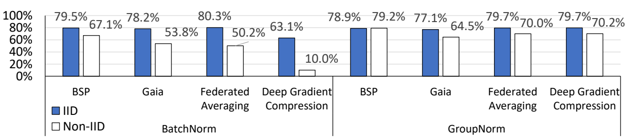


Figure 5. Top-1 validation accuracy with BatchNorm and GroupNorm for BN-LeNet over CIFAR-10 with 5 partitions.

First, GroupNorm successfully recovers the accuracy loss of BatchNorm with BSP in the Non-IID setting. As the figure shows, GroupNorm with BSP achieves 79.2% validation accuracy in the Non-IID setting, which is as good as the accuracy in the IID setting. This shows GroupNorm can be used as an alternative to BatchNorm to overcome the Non-IID data challenge for BSP. Second, GroupNorm dramatically helps the decentralized learning algorithms in the Non-IID setting as well. With GroupNorm, there is 14.4%, 8.9% and 8.7% accuracy loss for `Gaia`, `FederatedAveraging` and `DeepGradientCompression`, respectively. While the accuracy losses are still significant, they are better than their BatchNorm counterparts by an additive 10.7%, 19.8% and 60.2%, respectively.

Discussion. While our study shows that GroupNorm can be a good alternative to BatchNorm in the Non-IID setting, it is worth noting that BatchNorm is widely adopted in many DNNs. Hence, more study is needed to see if GroupNorm can replace BatchNorm for different applications and DNN models. As for other tasks such as recurrent (e.g., LSTM (Hochreiter & Schmidhuber, 1997)) and generative (e.g., GAN (Goodfellow et al., 2014)) models, other normalization techniques such as LayerNorm can be good options because *(i)* they are shown to be effective in these tasks and *(ii)* they are not dependent on minibatches.

6. Degree of Data Skew

In §4–§5, we studied a strict case of skewed label partitions, where each label only exists in a single data partition, *exclusively* (the one exception being our experiments with Flickr-Mammal). While this case may be a reasonable approximation for some applications (e.g., for FACE RECOGNITION, a person's face image may exist only in one data partition), it could be an extreme case for other applications (e.g., IMAGE CLASSIFICATION, as §2.2 shows). Here, we study how the problem changes with the degree of skew by controlling the fraction of the dataset that is non-IID (i.e., partitioned using labels, §3). Figure 6 shows the CIFAR-10 validation accuracy of GN-LeNet (our name for BN-LeNet with GroupNorm replacing BatchNorm) in the 20%, 40%, 60% and 80% non-IID setting. We make two observations.

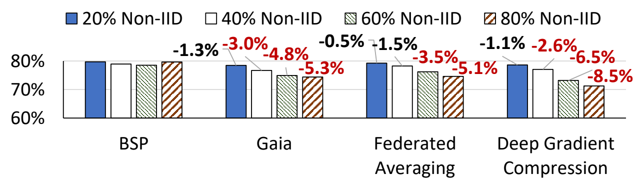


Figure 6. Top-1 validation accuracy for GN-LeNet over CIFAR-10, varying the degree of skew. Each "-x%" label indicates the accuracy loss relative to BSP in the IID setting. Note: The y-axis starts at 60% accuracy.

1) Partial non-IID data is also problematic. We see that for all three decentralized learning algorithms, partial non-IID data can still cause major accuracy loss. Even with a small degree of non-IID data such as 40%, we still see 1.5%–3.0% accuracy loss. Thus, the problem of non-IID data does not occur only with exclusive label partitioning, and the problem exists in the vast majority of practical settings.

2) Degree of skew often determines the difficulty level of the problem. The model accuracy gets worse with higher degrees of skew, and the accuracy gap between 80% and 20% non-IID data can be as large as 7.4% (`DeepGradientCompression`). In general, we see that the problem becomes more difficult with higher degree of skew.

7. Our Approach: SkewScout

To address the problem of skewed label partitions, we introduce SkewScout, a general approach that enables communication-efficient decentralized learning over *arbitrarily* skewed label partitions.

7.1. Overview of SkewScout

We design SkewScout as a general module that can be seamlessly integrated with different decentralized learning algorithms, ML training frameworks, and ML applications. Figure 7 provides an overview of the SkewScout design.

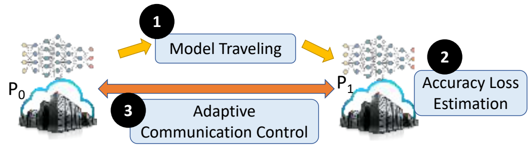


Figure 7. Overview of SkewScout

1. **Estimating the degree of skew.** As §6 shows, knowing the degree of skew is very useful to determine an appropriate solution. To learn this information, SkewScout periodically moves the ML model from one data partition (P_k) to another during training (*model traveling*, ❶ in Figure 7). SkewScout then evaluates how well a model performs on a remote data partition by evaluating the model accuracy with a subset of training data on the remote node. As we already know the training accuracy of this model in its original data partition, we can infer the *accuracy loss* in the remote data partition (❷).
2. **Adaptive communication control (❸).** Based on the estimated accuracy loss, SkewScout controls the amount of communication among data partitions to retain model quality. SkewScout controls the amount of communication by automatically tuning the hyper-parameters of the decentralized learning algorithm (§4.4). This tuning process essentially solves an optimization problem that aims to minimize communication among data partitions while keeping accuracy loss within a reasonable threshold (further details below).

In essence, SkewScout handles non-IID data partitions by controlling communication based on accuracy loss. SkewScout is agnostic to the source of the loss, which may be due to skewed label partitions or other forms of non-IID data (Appendix K). As long as increasing communication improves accuracy for the data skew, SkewScout should be effective in retaining model quality while minimizing communication.

7.2. Mechanism Details

We discuss the mechanisms of SkewScout in detail.

Accuracy Loss. The accuracy loss between data partitions represents the degree of model divergence. As §4.3 discusses, ML models in different data partitions tend to specialize for their training data, especially when we use decentralized learning algorithms to reduce communication.

We study accuracy loss under `Gaia`, for hyper-parameter choices T_0=2%, 5%, 10%, 20%, in the IID and non-IID settings. We find that accuracy loss changes drastically from the IID setting (0.4% on average) to the Non-IID setting (39.6% on average), and that lower T_0 results in smaller accuracy loss in the non-IID setting. See Appendix J for further details. Accordingly, we can use accuracy loss (i) to estimate how much the models diverge from each other (reflecting training data differences); and (ii) to serve as an objective function for communication control. The computation overhead to evaluate accuracy loss is quite small because we run inference with only a small fraction of training data, and we only do so once in a while (we empirically find that once every 500 mini-batches is frequent enough).

Communication Control. The goal of communication control is to retain model quality while minimizing communication among data partitions. We achieve this by solving an optimization problem, which aims to minimize communication while keeping the *accuracy loss* below a small threshold σ_{AL} so that we can control model divergence caused by non-IID data partitions. We solve this optimization problem periodically after we estimate the accuracy loss with model traveling. Specifically, our target function is:

$$\operatorname*{argmin}_{\theta}\left(\lambda_{AL}\left(\mathtt{max}(0, AL(\theta)-\sigma_{AL})\right)+\lambda_C\frac{C(\theta)}{CM}\right) \quad (1)$$

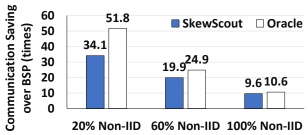
where $AL(\theta)$ is the accuracy loss based on the previously selected hyper-parameter θ (we memoize the most recent value for each θ that has been explored), $C(\theta)$ is the amount of communication given θ, CM is the communication cost for the whole ML model, and λ_{AL}, λ_C are given parameters to determine the weights of accuracy loss and communication, respectively. We can employ various algorithms with Equation 1 to select θ, such as hill climbing, stochastic hill climbing (Russell & Norvig, 2020), and simulated annealing (Van Laarhoven & Aarts, 1987).

7.3. Evaluation Results

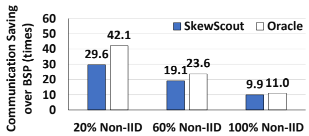
We implement and evaluate SkewScout in a GPU parameter server system (Cui et al., 2016) based on Caffe (Jia et al., 2014). We evaluate several aforementioned auto-tuning algorithms and we find that hill climbing provides the best results. As our primary goal is to minimize accuracy loss, we set $\lambda_{AL} = 50$ and $\lambda_{AC} = 1$. We set $\sigma_{AL} = 5\%$ to tolerate an acceptable accuracy variation during training, which does not reduce the final validation accuracy.

We compare SkewScout with two other baselines: (1) `BSP`: the most communication-heavy approach that retains model accuracy in all Non-IID settings; and (2) `Oracle`: the ideal, yet unrealistic, approach that selects the most communication-efficient θ that retains model accuracy, by *running all possible* θ in each setting prior to measured execution. Figure 8 shows the communication savings over `BSP` for both SkewScout and `Oracle` when training with `Gaia`. Note that all results achieve *the same* validation accuracy as `BSP`. We make two observations.

First, SkewScout is much more effective than `BSP` in handling Non-IID settings. Overall, SkewScout achieves 9.6–34.1× communication savings over `BSP` in various Non-IID settings without sacrificing model accuracy. As expected, SkewScout saves more communication with less skewed data because SkewScout can safely loosen communication.



(a) AlexNet



(b) GoogLeNet

Figure 8. Communication savings over BSP with SkewScout and `Oracle` for training with CIFAR-10. All results achieve the same accuracy as BSP in the IID setting.

Second, SkewScout is not far from the ideal `Oracle` baseline. Overall, SkewScout requires only 1.1–1.5× more communication than `Oracle` to achieve the same model accuracy. SkewScout cannot match the communication savings of `Oracle` because: (i) SkewScout does model traveling periodically, which leads to some overhead; and (ii) for some θ, high accuracy loss at the beginning can still lead to a high accuracy model, which SkewScout cannot foresee. As `Oracle` requires *many* runs in practice, we conclude that SkewScout is an effective, realistic one-pass solution for decentralized learning over non-IID data partitions.

8. Related Work

To our knowledge, this is the first study to show that skewed label partitions across devices/locations is a fundamental and pervasive problem for decentralized learning. Our study investigates various aspects of this problem, such as a real-world dataset, decentralized learning algorithms, batch normalization, and data skew, as well as presenting our SkewScout approach. Here, we discuss related work.

Large-scale systems for centralized learning. There are many large-scale ML systems that aim to enable efficient ML training over *centralized* datasets using communication-efficient designs, such as relaxing synchronization requirements (Recht et al., 2011; Ho et al., 2013; Goyal et al., 2017) or sending fewer updates to parameter servers (Li et al., 2014a;b). These works assume the training data are centralized so they can be easily partitioned among the machines performing the training in an IID manner (e.g., by random shuffling). Hence, they are neither designed for nor validated on non-IID data partitions.

Decentralized learning. Recent prior work proposes communication-efficient algorithms (e.g., (Hsieh et al., 2017; McMahan et al., 2017; Shokri & Shmatikov, 2015; Lin et al., 2018; Tang et al., 2018)) for ML training over *decentralized* datasets. However, as our study shows, these decentralized learning algorithms lose significant model accuracy in the Non-IID setting (§4). Some recent work studies the problem of non-IID data partitions. For example, instead of training a global model to fit non-IID data partitions, federated multi-task learning (Smith et al., 2017) trains local models for each data partition while leveraging other data partitions to improve model accuracy. However, this approach sidesteps the problem for global models, which are essential when a local model is unavailable (e.g., a brand new partition without training data) or ineffective (e.g., a partition with too few training examples for a class). Several recent works show significant accuracy loss for `FederatedAveraging` over non-IID data, and some propose algorithms to improve `FederatedAveraging` over non-IID data (Zhao et al., 2018; Li et al., 2019; Shoham et al., 2019; Karimireddy et al., 2019; Liang et al., 2019; Li et al., 2020a; Wang et al., 2020; Khaled et al., 2020). While the result of these works aligns with our observations, our study *(i)* broadens the problem scope to a variety of decentralized learning algorithms, ML applications, DNN models, and datasets, *(ii)* explores the problem of batch normalization and possible solutions, and *(iii)* designs and evaluates SkewScout, which can also complement the aforementioned algorithms by controlling their hyper-parameters over arbitrarily skewed data partitions.

Non-IID dataset. Recent work offers non-IID datasets to facilitate the study of federated learning. For example, LEAF (Caldas et al., 2018) provides datasets that are partitioned in various ways. Luo et al. release 900 images collected from cameras in different locations, and they show severe skewed label distribution across cameras (Luo et al., 2019). Our study on geo-tagged mammals on Flickr shows the same problem at a much larger scale, and our dataset broadens the scope to include geo-distributed learning.

9. Conclusion

As most timely and relevant ML data are generated at different physical locations, and often infeasible/impractical to collect centrally, decentralized learning provides an important path for ML applications to leverage such data. However, decentralized data is often generated at different contexts, which leads to a heavily understudied problem: *non-IID training data partitions*. We conduct a detailed empirical study of this problem for skewed label partitions, revealing three key findings. First, we show that training over skewed label partitions is a fundamental and pervasive problem for decentralized learning, as all decentralized learning algorithms in our study suffer major accuracy loss. Second, we find that DNNs with batch normalization are particularly vulnerable in the Non-IID setting, with even the most communication-heavy approach being unable to retain model quality. We further discuss the cause and a potential solution to this problem. Third, we show that the difficulty level of this problem varies greatly with the degree of skew. Based on these findings, we present SkewScout, a general approach to minimizing communication while retaining model quality even for non-IID data. We hope that the findings and insights in this paper, as well as our open source code and dataset, will spur further research into the fundamental and important problem of non-IID data in decentralized learning.

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