Abstract

When a neural network is partitioned and distributed across physical nodes, failure of physical nodes causes the failure of the neural units that are placed on those nodes, which results in a significant performance drop. Current approaches focus on resiliency of training in distributed neural networks. However, resiliency of inference in distributed neural networks is less explored. We introduce ResiliNet, a scheme for making inference in distributed neural networks resilient to physical node failures. ResiliNet combines two concepts to provide resiliency: skip connection in residual neural networks, and a novel technique called failout, which is introduced in this paper. Failout simulates physical node failure conditions during training using dropout, and is specifically designed to improve the resiliency of distributed neural networks. The results of the experiments and ablation studies using three datasets confirm the ability of ResiliNet to provide inference resiliency for distributed neural networks.

1. Introduction

Deep neural networks (DNNs) have boosted the state-of-the-art performance in various domains, such as image classification, segmentation, natural language processing, and speech recognition (Krizhevsky et al., 2012; Hinton et al., 2012; LeCun et al., 2015; Sutskever et al., 2014). In certain DNN-empowered IoT applications, such as image-based defect detection or recognition of parts during product assembly, or anomaly behavior detection in a crowd, the inference task is intended to run for a prolonged period of time. In these applications, a recent trend has been to partition and distribute the neural network over physical nodes along an edge-to-cloud path (e.g. on edge servers) so that the forward-propagation occurs on in-network while the data traverses toward the cloud (Teerapittayanon et al., 2017; Tao and Li, 2018). This distributed DNN architecture is motivated by two observations: Firstly, deploying DNNs directly onto IoT devices for huge multiply-add operations is often infeasible, as many IoT devices are low-powered and resource-constrained (Zhou et al., 2019a). Secondly, placing the DNNs in the cloud may not reasonable for such prolonged inference tasks, as the raw data, which is often large, has to be continuously transmitted from IoT devices to the DNN model in the cloud, which results in the high consumption of network resources and possible privacy concerns (Jeong et al., 2018; Teerapittayanon et al., 2017).

A natural question that arises within this setting is whether the inference task of a distributed DNN is resilient to the failure of individual physical nodes. Physical nodes could fail due to power outages, cable cuts, natural disasters, or hardware/software failures. Providing failure-resiliency for such inference tasks is vital, as physical node failures are more probable during a long-running inference task. Failure of a physical node causes the failure of the DNN units that are placed on the node, and is especially troublesome for IoT applications that cannot tolerate poor performance while the physical node is being recovered. The following question is the topic of our study. How can we make distributed DNN inference resilient to physical node failures?

Several frameworks have been developed for distributed training of neural networks (Abadi et al., 2016; Paszke et al., 2017; Chilimbi et al., 2014). On the other hand, inference in distributed DNNs has emerged as an approach for DNN-empowered IoT applications. Providing failure-resiliency during inference for such IoT applications is crucial. Yousefpour et al. (2019) introduce the concept of skip hyperconnections in distributed DNNs that provides some failure-resiliency for inference in distributed DNNs. Skip hyperconnections skip one or more physical nodes in the vertical hierarchy of a distributed DNN. These forward connections between non-subsequent physical nodes help in making distributed DNNs more resilient to physical failures, as they provide alternative pathway for information when a physical node has failed. Although superficially they might seem similar to skip connections in residual networks (He et al., 2016a), skip hyperconnections serve a completely different purpose. While the former aim at solving the v-
ishing gradient problem during training, the latter are based on the underlying insight that during inference, if at least a part of the incoming information for a physical node is present (via skip hyperconnections), given their generalization power, the neural network may be able to provide a reasonable output, thus providing failure-resiliency.

A key observation in the aforementioned work is that the weights learned during training using skip hyperconnections are not aware that there might be physical node failures. In other words, the information about failure of physical nodes is not used during training to make the learned weights aware of such failures. As such, skip hyperconnections by themselves do not make the learned weights more resilient to physical failures, as they are just a way to diminish the effects of losing the information flow at inference time.

Motivated by this limitation, we introduce ResiliNet, which utilizes a new regularization scheme we call failout, in addition to skip hyperconnections, for making inference in distributed DNNs resilient to physical node failures. Failout is a regularization technique that during training "fails" (i.e. shuts down) the physical nodes of the distributed DNN, each hosting several neural network layers, thus simulating inference failure conditions. Failout effectively embeds a resiliency mechanism into the learned weights of the DNN, as it forces the use of skip hyperconnections during failure. The training procedure using failout could be applied offline, and would not necessarily be done during runtime (hence, shutting down physical nodes would be doing so in simulation). Although in (Yousefpour et al., 2019) skip hyperconnections are always active both during training and inference, in ResiliNet skip hyperconnections are active during training, but are only active during inference when the physical node that they bypass fail (for bandwidth savings).

Experimental results using three datasets show that ResiliNet minimizes the degradation impact of physical node failures during inference, under several failure conditions and network structures. Finally, through ablation studies, we explore the hyperparameters of ResiliNet, including the rate of failout, the weight of hyperconnections, and sensitivity of skip hyperconnections. ResiliNet’s major novelty is in providing failure-resiliency through special training procedures, rather than traditional “system-based” approaches of redundancy, such as physical node replication or backup.

2. Resiliency-based Regularization for DNNs

In this section we introduce the building blocks of the ResiliNet architecture, namely distributed neural networks, skip hyperconnections, and failout regularization.

2.1. Distributed neural networks

A distributed DNN is a DNN that is split according to a partition map and distributed over a set of physical nodes (a form of model parallelism). This article studies the resiliency of previously-partitioned distributed DNN models during inference. We do not study the problem of optimal partitioning of a DNN; the optimal DNN partitioning depends on factors such as available network bandwidth, type of DNN layers, and the neural network topology (Hu et al., 2019; Kang et al., 2017; Zhou et al., 2019b). We do not consider doing any neural architecture search in this article.

Since a single distributed DNN resides on different physical nodes, during inference the vector of output values from one physical node must be transferred (e.g. through a TCP socket) to another physical node. The transfer link (pipe) between two physical nodes is called a hyperconnection (Yousefpour et al., 2019). Hyperconnections transfer information (e.g. feature maps) as in traditional connections between neural network layers, but through a physical communication network. Unlike a typical neural network connection that connects two units and transfers a scalar, a hyperconnection connects two physical nodes and transfers a vector of scalars. Hyperconnections are one of two types: simple or skip. A simple hyperconnection connects a physical node to the physical node that has the next DNN layer. Skip hyperconnections are explained next.

2.2. Skip Hyperconnections

The concept of skip hyperconnections is similar to that of skip connections in residual networks (ResNets) (He et al., 2016a). A skip hyperconnection (Yousefpour et al., 2019) is a hyperconnection that skips one or more physical nodes in a distributed neural network, forwarding the information to
a physical node that is further away in the distributed neural network structure. During training, the DNN learns to use the skip hyperconnections to allow an upstream physical node receive information from more than one downstream physical node. Consequently, during inference, if a physical node fails, information from the prior working nodes are still capable of propagating forward to upstream working physical nodes via these hyperconnections. Skip hyperconnections already provide some failure-resiliency, as shown by DFG framework described in (Yousefpour et al., 2019).

ResiliNet also uses skip hyperconnections, but in a slightly different manner from the DFG framework. Figure 1 shows ResiliNet’s skip hyperconnections setup during training and inference. During training, skip hyperconnections are always active, as shown with a solid arrow in Fig. 1a. The output of hyperconnection in this case is added to that of the simple hyperconnection. However, during inference, skip hyperconnections are only active when the physical node that they bypass fails (skip hyperconnection shown with dashed arrow in Fig. 1b). This setup in ResiliNet significantly saves bandwidth, compared to that of DFG, which requires skip hyperconnections to be always active. Figure 2 shows ResiliNet’s configurations of hyperconnections during inference for different distributed DNN architectures.

When performing operations on the output of hyperconnections, it may be necessary to match the dimensions of the hyperconnections. For distributed MLPs (multi-layer perceptrons), to match the dimension of the hyperconnections, we can do zero-padding or add a fully-connected layer. For distributed CNNs (convolutional neural networks), we can do zero-padding or $1 \times 1$ convolutions (He et al., 2016a).

2.3. Failout Regularization

In the DFG framework (Yousefpour et al., 2019), the information regarding failure of the physical nodes is not used during training to make the learned weights more aware of such failures. Although skip hyperconnections increase the failure-resiliency of distributed DNNs, they do not make the learned weights more prepared for such failures. This is because all neural network components are present during training, as opposed to inference time where some physical nodes may fail. In order to account for the learned weights being more adapted to specific failure scenarios, we introduce failout regularization, which simulates inference-time physical node failure conditions during training.

During training, failout “fails” (i.e., shuts down) a physical node, to make the learned weights more adaptive to such failures and the distributed neural network more failure-resilient. By “failing” a physical node, we mean temporarily removing the neural network components that reside on the physical node, along with all their incoming and outgoing connections. Failout’s training procedure could be done offline, and would not necessarily be employed during runtime. Therefore failing physical nodes would be temporarily removing their neural network components in simulation.

When the neural components of a given physical node shut down using failout, the neural layers of the upstream physical node that are connected to the failing physical node will not receive information from the failing physical node, forcing their weights to take into account this situation and utilize the received information from the skip hyperconnection. In other words, failout forces the information passage through the skip hyperconnections during training, hence adapting the weights of the neural network to account for these failure scenarios during inference. Note that if a physical node does not have a skip hyperconnection bypassing it, applying failout on it during training will not improve the failure-resiliency, as there is no alternative information path if the physical node fails. Thus, it is not required to apply failout on physical nodes that do not have skip hyperconnections bypassing them.

Formally, consider a neural network which is distributed over $V$ different nodes $v_i$, $i \in [1, V]$, where for each $v_i$, we define its failure rate (probability of failure) $f_i \in [0, 1]$. Following this, we define a binary mask $b$ with $V$ components, where its $i$-th element $b_i$ follows a Bernoulli distribution, with a mean equal to $1 - f_i$, that is $b_i \sim Ber(1 - f_i)$. During training, for each batch of examples, a new mask $b$ is sampled, and if $b_i = 0$, the neural components of physical node $v_i$ are dropped from computation ($v_i$’s output is set to zero in simulation), thus simulating a real failure scenario. Although, superficially, this procedure seems similar to dropout (Srivastava et al., 2014), failout removes a whole segment of neural components, including neurons and weights, and for an entirely different purpose of failure-resiliency. However, in dropout, randomly selected neurons
are removed for regularizing the neural network.

Another important distinction between failout and dropout is in their behavior during inference. In dropout, at inference, the weights of connections are multiplied by the probability of survival of their source neuron to account for model averaging from exponentially many thinned models. Furthermore, DNN units are not dropped during inference in dropout, making the model averaging a necessity. In contrast, failout does not multiply weights of hyperconnections by the probability of survival, since, during inference, physical nodes may fail, though not necessarily at the same rate as during training. Said differently, failout does not use the model ensemble analogy as used in standard dropout, hence does not need the mixed results of the model ensembles. To verify our hypothesis regarding failout, we conducted experiments using different datasets in a setting where the weights of hyperconnections are multiplied by the probability of survival of the physical nodes, and we observed a shear reduction in performance.

3. Experiments

In this section we describe the experiment scenarios, datasets, experiment setup, evaluation results, and ablation studies for ResiliNet. We will compare ResiliNet’s performance with that of DFG (Yousefpour et al., 2019) and vanilla (distributed DNN with no skip hyperconnections and no failout). We begin by describing the scenarios we used for the experiments and their corresponding datasets.

3.1. Scenarios and Datasets

We evaluate the resiliency of our approach in two relevant distributed DNN scenarios: vertically distributed MLP and vertically distributed CNN. We first describe each of the scenarios and the datasets used for each scenario.

Vertically distributed MLP: Figure 3a presents the DNN structure proposed for this scenario. This is the simplest scenario for a distributed DNN in which the MLP is split vertically across physical nodes.

For this scenario, we use the UCI health activity classification dataset (“Health” for short), described in (Banos et al., 2015). This dataset is an example of an IoT application for medical purposes where the inference task will run over a long period of time. The dataset is comprised of readings from various sensors placed at the chest, left ankle, and right arm of 10 patients. There are a total of 23 features, each corresponding to a type of data collected from sensors. For this experiment, we split a DNN that consists of ten hidden layers of width 250, over 4 physical nodes as follows. The physical node \( n_1 \) hosts one hidden layer, \( n_2 \) two, \( n_3 \) three, and \( n_4 \) four (also summarized in Table 1).

The dataset is labeled with the 12 activities a patient is performing at a given time, and the task is to classify the type of activity. We remove the activities that do not belong to one of the classes. After reprocessing, the dataset contains 343,185 data points and is roughly uniformly distributed across each class. Hence, we use a standard cross-entropy loss function for the classification. For evaluation, we separate data into train, validation, and test with an 80/10/10 split. We use the validation set to select the model with the highest accuracy, and report performance on the test set.

Vertically distributed CNN: Figure 3b presents the neural network setup for this scenario and how the CNN is split. CNNs are used in most state-of-the-art applications in computer vision, and are relevant to vision-based IoT applications, such as video surveillance, where the inference task will run for a long period of time.

For this scenario, we use two datasets, ILSVRC and CIFAR-10. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset (Russakovsky et al., 2015), labeled “ImageNet” in this paper, contains 1.35 million images, where 1.2 million images are set aside for training, 50,000 for validation, and 100,000 for testing. The images belong to 1000 different categories. As the testing set is not publicly available, we report performance on the validation set.

We utilize the ILSVRC dataset for measuring the performance of ResiliNet in distributed CNNs. However, for ablation studies for distributed CNNs, we use the CIFAR-10 dataset, since we run several iterations of experiments with different hyperparameters, and training a model with ILSVRC dataset is computationally expensive.

The CIFAR-10 dataset consists of 60,000 images that correspond to 10 objects (Krizhevsky, 2009). The dataset is split into 50,000 examples for training and 10,000 for testing. In both datasets, the distribution of data points is uniform,
hence we used a cross-entropy loss for training. We also employ data augmentation to improve model generalization.

For CIFAR-10 and ImageNet datasets, we use the MobileNetV1 CNN architecture (Howard et al., 2017) and split it across 3 physical nodes. For better analysis of skip hyper-connections and failout, we chose version 1 of MobileNet (MobileNetV1), as it does not have any of the skip connections that are present in MobileNetV2. The MobileNetV1 architecture has 13 “stacked layers”, each with the following six layers: depth-wise convolution, batch normalization, ReLU, convolution, batch normalization, and ReLU. We partition these 13 stacked layers across the three physical nodes (Fig. 3b): $m_1$ contains three stacked layers, $m_2$ five, and $m_3$ five plus the remaining layers (average pooling, fully-connected, and softmax). One of the hyperparameters for MobileNetV1 is the $\alpha$ that adjusts the width of the CNN by changing the number of filters per layer. $\alpha = 0.75$ was chosen in order to have a small enough computational footprint, while still maintaining a high accuracy.

3.2. Experiment Settings

We implemented our experiments using TensorFlow and Keras on Amazon Web Service EC2 p3.8xlarge instance, which has 4 GPUs, 32 vCPUs, and 244 GiB RAM. All of the models are trained via stochastic gradient descent using the Adam optimizer. Batch sizes of 1024, 128, and 1024 are used for the Health, CIFAR-10, and ImageNet experiments, respectively. The learning rate of 0.001 is used for the health activity classification and CIFAR-10 experiments. Learning rate decay with initial rate of 0.01 is used for the ImageNet experiment. The image size of $160 \times 160 \times 3$ pixels is used for the ImageNet experiment. The rate of failout for ResiliNet is set to 5% (other rates of failout are explored later in ablation studies).

We propose three different failure settings outlined in Table 1. A failure setting is a tuple, where each element $i$ is the probability that the physical node $v_i$ fails during inference. The setting Normal represents a reasonable network, where probability of failure is not arguably low, while the settings Poor and Hazardous represent failure settings (only for experiments) when the failures are very frequent in the physical network. The failure probabilities of physical nodes are summarized in Table 1. We assume that the top physical node ($n_4$ in Fig. 3a or $m_3$ in Fig. 3b) is the cloud, and hence is always available.

3.3. Performance Evaluation

Table 2 shows the performance of ResiliNet, DFG, and Vanilla for certain physical node failures. The fist two columns show the failing nodes, along with the probability of occurrence of those node failures under Normal failure setting. Recall that Vanilla is a distributed DNN that does not have skip hyperconnections and does not use failout. We assume that, when there is no information available to do the classification task due to failures, we do random guessing.

(a) Health: In the health activity classification experiment, we see that the failure of even a single physical node compromises the performance of Vanilla due to random guessing, resulting accuracy of around 8%. On the other hand, DFG and ResiliNet subvert Vanilla’s inability to pass data over failed physical nodes, thereby achieving significantly greater performance. The results also show that, in this experiment, ResiliNet performs better than DFG in all of the cases, except for when there is no failure. In certain physical nodes failures, such as when $n_1$, $n_2$, or {$n_1$, $n_3$} fail, ResiliNet greatly surpasses the accuracy of the both DFG and Vanilla, providing a high level of failure-resilience. When physical node failures {$n_1$, $n_2$} and {$n_2$, $n_3$} occur, even ResiliNet and DFG do not provide high accuracy, due to inaccessibility of the path for information flow.

It is worth noting that ResiliNet’s performance when there is no failure is marginally lower than that of Vanilla. We hypothesize that, since failout drops a significant portion of the neural network, it cannot help in regularizing the neural network when there are no failures, as opposed to standard dropout. A remarkable effect of the proposed scheme can be observed when $n_3$ fails. When this happens, both DFG and ResiliNet maintain accuracy above 92%, 5% less than the maximum accuracy, even though a significant portion of the neural network has failed. This may be an indication that the neural layers on node $n_3$ do not perform critical transformation on the data.

(b) ImageNet: We trained the three distributed CNN models, ResiliNet, DFG, and Vanilla, to reach near the state-of-the-art top-1 accuracy of 65.3\(^1\), when there is no failure. In the ImageNet experiment, since Vanilla has no additional pathways for the flow of information during any physical node failure, it is vastly outperformed by the other two methods in the case of any failure. This is similar to the poor performance of Vanilla during any failure in the health activity classification experiment. Furthermore, ResiliNet

| Experiment       | Health | ImageNet/CIFAR-10 |
|------------------|--------|-------------------|
| Nodes Order      | $[n_4, n_3, n_2, n_1]$ | $[m_3, m_2, m_1]$ |

**Table 1. Experiment settings**

| Failure Setting | Health | ImageNet/CIFAR-10 |
|-----------------|--------|-------------------|
| Normal          | $[0\%, 1\%, 4\%, 8\%]$ | $[0\%, 2\%, 4\%]$ |
| Poor            | $[0\%, 5\%, 9\%, 13\%]$ | $[0\%, 5\%, 16\%]$ |
| Hazardous       | $[0\%, 15\%, 20\%, 23\%]$ | $[0\%, 15\%, 20\%]$ |

\(^1\)https://github.com/tensorflow/models
Figure 5. Impact of hyperconnection weight in ResiliNet

### Table 2. Individual physical node failures

| Nodes   | Failing (%) | Accuracy (%) | ResiliNet | DFG | Vanilla |
|---------|-------------|--------------|-----------|-----|---------|
| Health  |             |              |           |     |         |
| None    | 87.43       | 97.28        | 97.90     | 97.85 |
| n₁      | 7.01        | 92.48        | 64.42     | 7.95 |
| n₂      | 3.64        | 86.52        | 22.49     | 7.99 |
| n₃      | 0.88        | 93.38        | 92.48     | 8.10 |
| n₁, n₂  | 0.32        | 8.12         | 8.2       | 7.93 |
| n₁, n₃  | 0.08        | 91.75        | 60.13     | 7.98 |
| n₂, n₃  | 0.04        | 7.86         | 7.98      | 7.97 |
| n₁, n₂, n₃ | 0.003   | 8.18         | 7.89      | 7.91 |
| ImageNet|             |              |           |     |         |
| None    | 94.08       | 65.01        | 64.86     | 65.06 |
| m₁      | 3.92        | 51.94        | 14.30     | 0.12 |
| m₂      | 1.92        | 45.41        | 10.23     | 0.09 |
| m₁, m₂  | 0.08        | 0.11         | 0.10      | 0.09 |

Table 3. Impact of fault rate in ResiliNet. Numbers represent average accuracy in %.

| Fault Rate | Experiment | Health | CIFAR-10 | Health | CIFAR-10 | Health | CIFAR-10 | Health | CIFAR-10 |
|------------|------------|--------|----------|--------|----------|--------|----------|--------|----------|
| N/A        | N/A        | 97.07  | 86.61    | 95.92  | 85.69    | 82.83  | 78.53    | 63.59  | 67.34    |
| 5%         | N/A        | 95.95  | 85.99    | 94.33  | 85.02    | 80.37  | 77.53    | 61.31  | 65.99    |
| 10%        | Poor       | 94.11  | 85.21    | 92.09  | 83.85    | 77.40  | 75.92    | 58.61  | 63.93    |
| 30%        | Hazardous  | 92.51  | 83.90    | 90.81  | 82.51    | 77.40  | 75.92    | 58.61  | 63.93    |
| 50%        | N/A        | 92.48  |          |        |          |        |          |        |          |

shows remarkably better performance than DFG, when m₁ or m₂ fails; ResiliNet maintains high accuracy, while DFG experiences a sheer performance drop. This illustrates the benefit of failout for resiliency. As expected, with the failure of m₂, the accuracy drops more, as m₂ hosts 5 stacked layers of the distributed CNN. Nevertheless, ResiliNet still maintains an accuracy of 45%, even when almost 38% of the neural network has failed. This again shows the notable failure-resiliency that is provided by ResiliNet.

In both health activity classification and ImageNet experiments, if there is a failure, ResiliNet’s accuracy is often significantly higher than than of DFG. Key observation 1: the reason is that, in DFG, with the absence of failout, the gradient of the loss function is passed through both skip and simple hyperconnections during training. However, in ResiliNet, by utilizing failout, the gradient of the loss function can no longer pass through the physical nodes that are failed, therefore they flow forcibly through the skip hyperconnections. This forces the training of the distributed DNN to emphasize the use of skip hyperconnections. This is likely why ResiliNet performs considerably better in the fully-vertical distributed neural networks.

Previously, we discussed and showed how the accuracy is affected when particular physical nodes fail. Nevertheless, some of the physical node failures are not as probable as others (e.g. multiple physical nodes failure vs. single physical node failure), and hence it is interesting to see the average accuracy. Fig. 4 shows the average accuracy of the three methods under different failure settings, with 10 iterations for the health activity classification experiment, and 2 iterations for the ImageNet experiment. Key result 1: as expected, in both Health and ImageNet experiments, ResiliNet seems to outperform DFG and Vanilla. The high performance of ResiliNet is more evident in severe node failure conditions.

### 3.4. Ablation Studies

Now that the validity of failout has been empirically shown to provide an increase in failure-resiliency of distributed neural networks, we now investigate the importance of individual skip hyperconnections, their weights, as well as the optimal rate of failout. To do so, we raise three important questions in what follows, and empirically provide answers to these questions. We use the CIFAR-10 dataset for ablation studies of the distributed CNN, and use Health for ablation studies of distributed MLPs.

1. **What is the best choice of weights for the hyperconnections?** Hyperconnections can have weights, similar to the weights of the connections in neural networks. We begin by assessing the choice of weights of the hyperconnections. Although by default, the weight of hyperconnections in ResiliNet is 1, we pondered if setting the weights relative to the reliability of their source physical nodes could improve the accuracy. Reliability of a physical node vᵢ is rᵢ = (1 – pᵢ), where pᵢ is the probability of failure of node vᵢ. We proposed two heuristics, called “Relative Reliability” and “Reliability,” that are described as follows:

Consider two physical nodes v₁ and v₂ feeding data through hyperconnections to physical node v₃. If physical node v₁ is less reliable than physical node v₂ (r₁ < r₂), setting v₁’s hyperconnections weight with a smaller value than that of v₂ may improve the performance. Thus, for the hyperconnection weight connecting node v₁ to node v₃, in Reliability heuristic, we set \( \widetilde{w}_{ij} = r_j \), where \( \widetilde{w}_{ij} \) denotes the weight of hyperconnection from physical node vᵢ to node vⱼ. Comparably, in Relative Reliability heuristic, we set \( \widetilde{w}_{ij} = \frac{r_i}{\sum_{k \in H_j} r_k} \), where \( H_j \) is the set of incoming hyperconnection indices to the physical node vⱼ.

We experiment with the following four hyperconnection weight schemes in ResiliNet for 10 runs: (1) weight of 1, (2) Reliability heuristic, (3) Relative Reliability heuristic, and
Figure 6. Ablation studies for analyzing sensitivity of ResiliNet’s skip hyperconnections in (a) health activity classification experiment, (b) CIFAR-10 experiment. The charts show average accuracy (with error bars showing standard deviation). The tables to the right of the charts show the present skip hyperconnections in each skip hyperconnection configuration. (Notation: letters indicate the source physical node of the corresponding skip hyperconnection)

(4) uniform random weight between 0 and 1. **Key result 2:** surprisingly, all of the four hyperconnection weight schemes resulted in similar performance. Since all of the values for average accuracy are similar in these experiments, we report in Fig. 5 the standard deviation among these weight schemes in ResiliNet.

We see that the standard deviation among the weight schemes is negligible, constantly below 1%. This suggests that there may not be a significant difference in accuracy when using any of the reasonable weighting scheme (e.g. heuristic of 1). **Key observation 2:** we also experimented with a scheme in which the hyperconnection weight is uniformly and randomly distributed between 0 and 10, and observed that the accuracy dropped significantly for the distributed MLPs. **Key observation 3:** surprisingly, the accuracy of distributed CNNs stays in the same range as in other schemes, when hyperconnection weight is a uniform random number between 0 and 10. We hypothesize that, for distributed MLPs, a reasonable hyperconnection weight scheme is a scheme that assigns the weights of hyperconnections between 0 and 1. Nevertheless, further investigation may be required in different distributed DNN architectures to assess the full effectiveness of hyperconnection weights.

**2. What is the optimal rate of failout?** In this ablation experiment, we investigate the effect of failout by setting the rate of failout to fixed rates of 5%, 10%, 30%, 50%, and a varying rate of “Failure,” where the failout rate for a physical node is equal to its probability of failure during inference. **Table 3** illustrates the impact of failout rate in ResiliNet. **Key result 3:** in all failure settings, we can see that the failout rate of 5% achieves the highest accuracy, and higher failout rate results in lower accuracy. **Key observation 4:** we hypothesize that, since a significant portion of the DNN is dropped during training when using failout, higher failout rate results in lower accuracy, as opposed to standard dropout. In standard dropout, the dropout rates are generally higher than 5%, because individual neurons are dropped with such rates, which are small part of the DNN. **Key observation 5:** based on our preliminary experiments, we conclude that the optimal failout rate should be seen as a hyperparameter, and be tuned for the experiment.

3. **Which skip hyperconnections are more critical?** It is important to see which skip hyperconnections in ResiliNet are more critical, thereby contributing more to the resiliency of the distributed neural network. This is helpful for certain scenarios in which having all skip hyperconnections is not possible (e.g. due to cost or communication constraints). To perform these experiments, we shut down (i.e. disconnect) a certain configuration of skip hyperconnections while keeping other skip hyperconnections active and every experiment setting the same, to see changes in the performance. The results are presented in Fig. 6. The bar charts show the average accuracy of 10 runs, under different “configs” in which a certain combination of skip hyperconnections are shut down. The configuration of the present skip hyperconnections are shown in the tables next to the bar charts. Letters in the tables indicate the source physical node of the skip hyperconnection. In the health activity classification experiment, since there are three skip hyperconnections in the distributed neural network, there are eight possible configurations of skip hyperconnections (“Config 1” through “Config 8”). Similarly, in the CIFAR-10 experiment, we consider all four configurations.

In the health activity classification (Fig. 6a), we can see a uniform accuracy gain, when going from Config 1 towards Config 8. We can also see that, by looking at Config 2 through Config 4, if only one skip hyperconnection is allowed in a scenario, it should be the skip hyperconnection
from input to $n_2$ (labeled as $i$). This is also evident when comparing Config 5 and Config 6: the skip hyperconnection from input to $n_2$ is more critical. In the Hazardous reliability scenario, a proper subset of two skip hyperconnections can achieve up to a 28% increase in average accuracy (Config 1 vs. Config 6). **Key result 4**: this hints that individual skip hyperconnections are more important when there are more failures in the network.

In the CIFAR-10 experiment, we also observe a uniform accuracy increase, when going from Config 1 towards Config 4. We can see that the skip hyperconnection from input to $n_2$ is more critical that the skip hyperconnection from $m_1$ to $m_3$ (Config 2 vs. Config 3). Nonetheless, if both skip hyperconnections are present (Config 4), the performance is at its peak.

This preliminary ablation study demonstrate that, by searching for particular critical subset of skip hyperconnections in a distributed neural network, especially in the Hazardous reliability scenarios, we can achieve a large increase in the average accuracy. We point the interested reader to (He et al., 2016b) for more information on ablation studies of skip connections in neural networks.

This concludes the discussion of our experiments. In the next section we explain the state of the art in this direction, and we position our work’s novelty in the literature.

4. Related Work

The related work in this space can be categorized in the following groups.

a. **Distributed Neural Networks**. Training of distributed neural networks has received significant attention (Abadi et al., 2016; Paszke et al., 2017; Chilimbi et al., 2014). Resilient distributed training against adversaries are studied in (Chen et al., 2018; Damaskinos et al., 2019). Nevertheless, inference in distributed neural networks is less explored, primarily due to the emerging application scenarios that need ongoing and long inference tasks (Teerapittayanon et al., 2017; Morshed et al., 2017; Liu et al., 2018; Tao and Li, 2018; Hu et al., 2019; Dey et al., 2019).

b. **Neural Network Fault Tolerance**. A related concept to failure is fault, which is when units or weights become defective (i.e. stuck at a certain value, or random bit flip). Studies on fault tolerance of neural networks date back to the early 90s, and are limited to mathematical models of small neural networks (e.g. neural networks with one hidden layer or unit-only and weight-only faults) (Mehrotra et al., 1994; Bolt, 1992; Phatak and Koren, 1995).

c. **Neural Network Robustness**. A line of research related to our study is robust neural networks (Goodfellow et al., 2015; Szegedy et al., 2014; Cisse et al., 2017; Basiani et al., 2016; El Mhamdi et al., 2017). Robustness in neural networks has gained considerable attention lately, and it is especially important when the neural network are to be developed in commercial products. These studies are primarily focused on adversarial examples, examples that are only slightly different from correctly classified examples drawn from the data distribution. Despite the relation to our study, we are not focusing on robustness of neural network to adversarial examples. We study resiliency of distributed DNN inference in the presence of failure of a large group of neural network units. **DFG** framework in (Yousefpour et al., 2019) uses skip hyperconnections for failure-resiliency of distributed DNN inference. We showed how ResiliNet differs from **DFG** in skip hyperconnections setup, and in its novel use of failout to provide even more failure-resiliency.

d. **Regularization Methods**. Some regularization methods that implicitly increase robustness are dropout (Srivastava et al., 2014), dropConnect (Wan et al., 2013), and zoneout (Krueger et al., 2016). Although there are similarities between failout and these methods in terms of the regularization procedure, these methods largely differ in spirit from ours. In particular, although during training, dropout turns off neurons and dropConnect discards weights, they both enable an ensemble of models for regularization. On the other hand, failout shuts down an entire physical nodes in a distributed neural network to simulate actual failures in the physical network, for providing failure-resiliency. The focus of zoneout is on regularizing recurrent neural networks, an approach that is not designed for failure-resiliency.

5. Conclusion

We presented ResiliNet, a framework for providing failure-resiliency of distributed DNN inference that combines two concepts: skip hyperconnections and failout. We saw how ResiliNet can improve the failure-resiliency of distributed MLPs and distributed CNNs. We also observed experimentally that, the weight of hyperconnections may not change the performance of distributed DNNs if the hyperconnections weights are chosen in certain range. We also observed that the rate of failout should be seen as a hyperparameter and be tuned. Finally, we observed that some skip hyperconnections are more critical than others, especially under more extreme failure scenarios.

**Limitations**: ResiliNet may take longer to converge, due to its failout regularization procedure. Moreover, if a distributed DNN is already trained, it needs to be re-trained with skip hyperconnections and failout; though, the training can be done offline.

**Future Work**: We view ResiliNet as an important first step in studying failure-resiliency in distributed DNNs. This study opens several paths for related research opportunities.
Firstly, it is interesting to study the distributed DNNs that are both horizontally and vertically distributed. Moreover, finding optimal hyperconnection weights through training (not through heuristics) may be a future research direction. Finally, instead of having only skip hyperconnection to bypass a node, we can have a skip layer, a layer to approximate the neural components of a failed physical node.

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