Calibrated BatchNorm: Improving Robustness Against Noisy Weights in Neural Networks

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Abstract

Analog computing hardware has gradually received more attention by the researchers for accelerating the neural network computations in recent years. However, the analog accelerators often suffer from the undesirable intrinsic noise caused by the physical components, making the neural networks challenging to achieve ordinary performance as on the digital ones. We suppose the performance drop of the noisy neural networks is due to the distribution shifts in the network activations. In this paper, we propose to recalculate the statistics of the batch normalization layers to calibrate the biased distributions during the inference phase. Without the need of knowing the attributes of the noise beforehand, our approach is able to align the distributions of the activations under variational noise inherent in the analog environments. In order to validate our assumptions, we conduct quantitative experiments and apply our methods on several computer vision tasks, including classification, object detection, and semantic segmentation. The results demonstrate the effectiveness of achieving noise-agnostic robust networks and progress the developments of the analog computing devices in the field of neural networks.

1 Introduction

The rapid progress of deep neural networks has aroused the interest in discovering suitable hardware devices for neural network inference which heavily demands computational resources and energy consumption. As the widespread deployment of network models on a variety of edge devices, it is urgent to design adequate hardware to satisfy the needs. In addition to the widely-used digital circuits (e.g. GPU) which have already been well developed, analog computing has attracted more attention in recent years since non-volatile memory devices are favourable in accelerating the inference of neural networks (Shafiee et al., 2016; Nomura et al., 2018; Angizi et al., 2019). In comparison to the digital platforms, process in-memory (PIM) analog computing has demonstrated orders of speed acceleration and lower power consumption, which allows it to become the reasonable choice to be employed for the neural network inference.

The imprecise analog computations result in intolerable performance drop of the neural networks and make the replacement of the digital circuits impractical despite the advantages of analog computing in

Preprint. Under review.
speed and power consumption. The performance degradation is due to the undesirable intrinsic noise inherent in the physical components of the analog devices. Previous work (Joshi et al., 2019) proposed to finetune the neural networks after the conventional training phase. Model weights were injected with Gaussian noise to simulate the analog computing scheme while finetuning. The proposed noisy-training allowed the networks to be robust to the noise caused by the analog devices during the inference. However, it is unrealistic to acquire the attributes of the noise beforehand and simulate the injected noise based on the prior knowledge in the noisy-training. In addition, noisy-trained networks are exclusively fit to a certain noise scale and further finetuning is required for different ones. The process of finetuning is inefficient as it demands additional training time and computing resources on top of the original training phase. As a result, the inefficiency and the unaffordable cost of noisy-training are unsatisfactory in progressing the analog computing into practice.

We assume the noise shifts the distributions of the activations away from the ‘clean’ ones without any noise, causing the performance drop in the neural networks. To verify our hypothesis, we demonstrate the distance of the distributions between the clean and the noisy activations as the green bars in Figure 1, where the distance is measured by Kullback-Liebler and Jensen-Shannon divergence. It is obvious that the noisy activations are significantly disturbed by the noise and shifted far away from the clean ones. Additionally, since BatchNorm (Ioffe & Szegedy, 2015) is capable of normalizing the mismatched distributions of the activations among mini-batches, we discover it appropriate and advantageous to alleviate the noise interference. In this paper, we propose to calibrate the BatchNorm statistics to rectify the disturbed activation distributions. The noise would make the running estimates of mean and variance inaccurate and therefore deactivates the normalization effect of BatchNorm layers. By recalculating the BatchNorm statistics, the calibrated BatchNorm is able to demonstrate its effectiveness in normalizing the mismatched distributions, as depicted in Figure 1 blue bars. Unlike the noisy-training which introduces additional resource for finetuning, the cost for keeping tack of the running estimates is negligible. Furthermore, our methods are easily adaptive to various scales of noise since it only requires to estimate the mean and variance of the activations in calibration. Therefore, calibrating the BatchNorm statistics is a practical approach to mitigate the noise interference in the neural network inference during analog computing.

We validate the performance of calibrating the BatchNorm statistics during analog computing in a variety of computer vision tasks, including image classification, object detection, and semantic segmentation. We demonstrate that our approach is able to alleviate the disturbing noise and improve the network robustness against the noisy weights. Additionally, we analyze the effectiveness of our approach employing on several representative models under variational noise in a number of experiments quantitatively and qualitatively. The contributions of this paper are summarized as follows:

Figure 1: Distribution distance between the activations in ResNet-34 before and after the noise injection. The blue and the green bars represent the divergence of the activations with and without applying our approach, respectively, while the red line illustrates the ratio between them. It can be observed that the distributions of the intermediate presentation with noise injected are far from the ones without any noise while the BatchNorm statistics are not calibrated, which results to the degradation in the final performance. In contrast, our approach calibrates the BatchNorm statistics and shifts the distributions close to the clean ones in both (a) KL divergence and (b) JS divergence.
We propose to recalculate the BatchNorm statistics to calibrate the shifted distributions caused by the noise during analog computing.

Our approach requires negligible additional cost for the BatchNorm statistics calibration, comparing to the unaffordable cost introduced by the noisy-training.

Our approach is adaptive to variational noise and merely a few adjustments are needed for different scales of noise.

The effectiveness and the efficiency allow calibrating the BatchNorm statistics a practical approach in developing the analog computing devices and putting it into practice.

The remainder of this paper is organized as follows. Section 2 discusses the research works related to this paper. Section 4 walks through the proposed methodology. Section 5 presents the experimental results and the ablation analysis. Section 6 concludes the paper.

2 Related Work

2.1 Improving Model Performance under Analog Computation

Applying analog computation to accelerate neural network in inference phase has been a active field for these years (Haensch et al., 2019). Except the works mentioned in previous paragraph which dedicated to design and ameliorate the hardware architecture, Klachko et al. (2019) explore the effect of common DNN component and training regularization techniques e.g., activation function, weight decay, Dropout(Srivastava et al., 2014), BatchNorm, on noise tolerance. Joshi et al. (2019) trained a neural network with injection noise to make the model weights less sensitive to variation of noise. Zhou et al. (2020) integrated the technique of knowledge distillation with noise injection training which can take advantage of the additive information of teacher model.

2.2 BatchNorm

 Tradition BatchNorm contains two stastical and two learnable components, mean, variance, scale and bias. In training phase, BatchNorm compute the mean $E[x]$ and variance $Var[x]$ of inputs batch $x$, then normalize each scalar feature independently, by making it have the mean of zero and the variance of 1. At last, scale and shift the normalized value $\hat{x}$ by the learnable parameters $\gamma$ and $\beta$. Meanwhile BatchNorm also records the exponential moving average (EMA) of mean and variance which can represent the training data distribution to normalize the inputs batch in inference phase.

BatchNorm (Ioffe & Szegedy, 2015) is a widely used normalization technique that can accelerate and stabilize the training of neural network by normalizing intermediate representations. However the effect of BatchNorm is not well-known, so recently works investigate the properties of BatchNorm to better understand the usage under different circumstances. (Guo et al., 2018) (Singh & Shrivastava, 2019) (Summers & Dinneen, 2019) propose methods that re-weigh the statistics between exponential moving average (EVM) and instant inference batch to mitigate training and testing data discrepancy occur in traditional BatchNorm. Xie et al. (2019) advanced the perspective that the distribution mismatch between clean examples and adversarial examples is a key factor that causes the performance degradation in modern neural networks containing the component of BatchNorm layer. and Frankle et al. (2020) investigated the expressive power of BatchNorm by only training BatchNorm parameters which merely account for 0.5% in the total number of model parameters. The model can only shift and rescale random features, but still achieves a fairly high accuracy.

\[
\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]} + \epsilon} \cdot \gamma + \beta
\]

3 Problem Formulation

The process of analog in-memory computing is limited by the non-idealities of variations originating from three main factors: 1.quality of wafer manufacturing, 2.stability of supply voltage, 3.temperature change, the combination of the above three factors leads to the floating of the computation. And NVM cell which is a key component in PIM-based DNN-accelerator used to store the weights of
neural network (Nomura et al., 2018) (Balaji et al., 2019) (Joshi et al., 2019), suffers variation of electro/thermo-dynamics during the read and write operations, the stored value has tendency to fluctuate from time to time due to the temperature change and the conductance drift of the device. The long-term fluctuation can be adjusted by refresh the hardware periodically. But the time-varing noise exist at smaller time granularity should be addressed. The simulated noises are described by two factors and the severity of noise can be controlled by noise scale $\eta_0$.

**Temporal fluctuation.** During the analog computing process, the instability of supply voltage, the temperature rises and falls may cause different degrees of computation error, this time-varying noise can be described by $N_T \sim N(\eta_0, \sigma_T^2)$ which is randomly sampled for each inference batch. And a noise temporal fluctuation level of 10% means that $\sigma_T = 0.1\eta_0$.

**Spatial fluctuation.** Due to the defect of the transistor manufacturing process, the analog computing noise may vary between different parts of chip, and this spatially-varying noises are introduced by sampling $N_S \sim N(\eta_0, \sigma_S^2)$ for once when the neural network is instantiated. And a noise spatial fluctuation level of 10% means that $\sigma_S = 0.1$.

So the weights of model after noise injection sampled from above two types of noise sources $W_{\text{noisy}}$ will be like the following eq(2):

$$W_{\text{noisy}} = W_{\text{orig}} + W_{\text{orig}} \cdot N_T \cdot N_S$$

(2)

4 Methodology

4.1 Inference with Calibrated BatchNorm

In analog computation noise setting, the noise is injected into model weights, makes the internal activation outputs distribution greatly differ from the original outputs of the clean weights. However, traditional BatchNorm performs the normalization by statistical results of training data, which are recorded without the exist of injected noises. Such statistical results can not successfully normalize the noisy outputs, make BatchNorm lose its effectiveness to adjust the output distribution of previous layer, so the noise will keep propagating, finally lead to wrong prediction. To mitigate the distribution mismatch between the noisy outputs and original outputs, we conjecture a perspective differ from traditional paradigm that use the training statistic or like (Guo et al., 2018) (Singh & Shrivastava, 2019) (Summers & Dinneen, 2019) which investigating the discrepancy between training and testing dataset, then integrate the training statistic with inference batch to gain additional improvement. We should not use the statistical results recorded in training phase when there is a obvious distribution shift, the mean and variance of inference batch need to be re-computed. So we perform calibration on training dataset, while inference on the training dataset with the noise is injected into the model, the statistic of such unstable analog computing environment can be recorded implicitly without knowing the actual setting of injected noise.

**Algorithm 1:** Calibrate the statistics of BatchNorm

```plaintext
for $x_i$ in $X_{\text{Train}}^{\text{Noisy}}$ do
1. $B_\sigma \leftarrow m \cdot B_\sigma + (1 - m) \cdot x_{i\sigma}$
2. $B_\mu \leftarrow m \cdot B_\mu + (1 - m) \cdot x_{i\mu}$
```

5 Experiments

5.1 Image Classification

In this section, experiments are conducted with widely-used dataset ImageNet-2012. (Krizhevsky et al., 2012) with different architectures. And we show the performance degradation when the noise is injected into model weights, and with the proposed method, the problem of distribution mismatch is eased, leads to favorable performance.

**Experimental Setup.** ImageNet-2012 is a large-scale dataset for image classification with 1k categories. The dataset contains roughly 1.3 million training images and 50k validation images of
Table 1: Validation acc (%) on ImageNet-2012.

|         | $\eta_0 = 0$ | $\eta_0 = 0.02$ | $\eta_0 = 0.04$ | $\eta_0 = 0.06$ | $\eta_0 = 0.08$ | $\eta_0 = 0.10$ |
|---------|--------------|----------------|----------------|----------------|----------------|----------------|
| ResNet-34 | 73.31        | 71.53         | 65.73         | 49.92         | 20.55         | 3.66           |
| ours     | 73.31        | 72.34         | 72.28         | 72.07         | 71.97         | 71.64          |
| ResNet-50 | 76.13        | 72.85         | 56.88         | 19.49         | 2.73          | 0.40           |
| ours     | 76.13        | 74.81         | 74.79         | 74.71         | 74.57         | 74.54          |
| ResNet-101 | 77.37       | 73.80         | 52.89         | 9.32          | 0.38          | 0.08           |
| ours     | 77.37        | 76.30         | 76.27         | 76.25         | 76.12         | 75.94          |
| WideResNet | 78.47       | 75.09         | 59.24         | 23.36         | 3.93          | 0.59           |
| ours     | 78.47        | 76.10         | 76.08         | 75.95         | 75.77         | 75.72          |
| MobileNet-v2 | 71.88    | 49.61         | 1.96          | 0.19          | 0.13          | 0.12           |
| ours     | 71.88        | 68.76         | 67.97         | 66.90         | 65.26         | 63.41          |

256x256 pixels. We use pytorch official pretrained models to conduct experiments and compare the performance of Calibrated BatchNorm with EMA (batch size = 256, momentum = 0.999) to the original model under the perturbation of noise injection of tempreal level $\sigma_T = 20\%$; spatial level $\sigma_S = 10\%$.

**Results.** Table 1. Shows that even in the large-scale dataset, the effect of calibrated BatchNorm is still notable. Besides, we find that the deeper the network, the more susceptible it was to noise due to the propagation of noise, as you can see the performance of different depths of ResNet 34, 50, 101 are 49.92%, 19.49%, 9.32% respectively under the noise scale of 0.06. And in the comparison between ResNet-50 and WideResNet-50-2, increasing the width of the network which is regarded to be more robust to adversarial examples (Gao et al., 2019), does not seem to have any benefit in terms of noise resistance in analog computing circumstance, because any additional parameters will be affected by the noise as well.

5.2 Object Detection

**Experimental Setup.** We use the official pretrainde YOLO-v3 (Redmon & Farhadi, 2018) implementaion as our detector. And conduct all the experiment on COCO-2014 dataset (Lin et al., 2014) with 80 object classes. Our detector is trained on trainval35k set with around 75k images, and evaluate on a held out set with 5k images. We report the standard COCO evaluation metrics for mean average precision mAP and mean average recall mAR with IoU threshold 0.5, comparing the performance of Calibrated BatchNorm with EMA (batch size = 8, momentum = 0.999) to the original model under the perturbation of noise injection of tempreal level $\sigma_T = 20\%$; spatial level $\sigma_S = 10\%$.

**Results.** Table 2. shows the results that even when the injection noise is severe, our method can still work in the difficult task of computer vision.

Table 2: Validation mAP, mAR (%) at 0.5 IoU on COCO-2014 val 5k.

|               | $\eta_0 = 0$ | $\eta_0 = 0.05$ | $\eta_0 = 0.10$ |
|---------------|--------------|----------------|----------------|
| mAP, mAR      | mAP, mAR     | mAP, mAR      | mAP, mAR      |
| Original model| 51.5 75.1    | 30.5 58.4     | 0.0 0.0       |
| Calibrated BatchNorm | 51.5 75.1 | 49.5 73.3 | 48.6 71.3 |

5.3 Semantic Segmentation

**Experimental Setup.** We use pytorch official FCN-ResNet101 (Long et al., 2014) that is pretrained on part of COCO dataset that shared the same classes with PASCAL VOC-2012 (Everingham et al.), we conduct the segmentation task on PASCAL VOC-2012 with 21 classes including background. We compare the performance of Calibrated BatchNorm with EMA (batch size = 1, momentum = 0.999)
to the original model under the perturbation of noise injection of temporal level $\sigma_T = 20\%$; spatial level $\sigma_S = 10\%$.

**Results.** Table 3. shows the results of semantic segmentation, the mIoU metric is more reliable than PixAcc, because mIoU focuses on classes excluding background. The experiment demonstrates that mIoU of original model drops drastically when noise scale increases, but Calibrated Batchnorm can handle the distribution shift even when the data come in a stream manner and in the task of semantic segmentation.

| $\eta_0$ | mIoU | PixAcc | $\eta_0$ | mIoU | PixAcc | $\eta_0$ | mIoU | PixAcc |
|---------|------|--------|---------|------|--------|---------|------|--------|
| 0       | 63.7 | 91.9   | 0.05    | 25.9 | 80.8   | 0.10    | 2.95 | 62.2   |
| Original model |       |        | Calibrated BatchNorm | 63.7 | 91.9 | 61.1 | 90.3 | 60.6 | 90.1 |

### 6 Conclusion

We advance a concept that formulate the imprecise process in memory computing as a distribution shift problem, and propose a effective way to calibrate the mismatching distribution. We conduct extensive experiments on important vision tasks including classification, object detection and semantic segmentation, the results demonstrate the significant improvement, further promote the progress the development of neural network in the analog computing field.
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