Towards Improving Generalization of Deep Networks via Consistent Normalization

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Abstract

Batch Normalization (BN) was shown to accelerate training and improve generalization of Convolutional Neural Networks (ConvNets), which typically use the “Conv-BN” couple as building block. However, this work shows a common phenomenon that the Conv-BN module does not necessarily outperform the networks trained without using BN, especially when data augmentation is presented in training. We find that this phenomenon occurs because there is inconsistency between the distribution of the augmented data and that of the normalized representation. To address this issue, we propose Consistent Normalization (CN) that not only retains the advantages of the existing normalization methods, but also achieves state-of-the-art performance on various tasks including image classification, segmentation, and machine translation. The code will be released to facilitate reproducibility.

1 Introduction

Batch normalization (BN) is an indispensable component of deep neural networks such as convolutional neural networks (ConvNets), achieving state-of-the-art results in various tasks such as image classification, speech recognition, and machine translation. BN imposes zero mean and unit variance of the representation of ConvNets, stabilizing the distributions of the learned representation to improve network training and generalization.

In the meantime, a ConvNet trained with BN is also typically trained by applying data augmentation such as random image cropping, cutout, and mixup, which have been proved to be effective to improve generalization of deep models. However, this work diagnoses the compatibility between BN and the data augmentation strategies widely employed, and shows that a ConvNet trained with the Conv-BN configuration does not necessarily outperform a network trained without BN, especially when data augmentation is presented. For example, as shown in Figure 1, we compare a deep network (i.e. ResNet-32) trained with or without data augmentation and BN on CIFAR-10. The network is trained by SGD using popular protocol without bells and whistles. We see that aggressive data augmentation brings about notable performance drop for ResNet-32, while ResNet-32 without BN, on the contrary, outperforms ResNet-32 with BN under this setting.

The above results disclose a common and undesirable phenomenon in training neural networks, due to the inconsistency between the distribution of the augmented data and that of the normalized representation after BN. To resolve this issue, we propose Consistent Normalization (CN), which is a normalization method that can maintain the consistency between different sets of samples generated by distinct data augmentation approaches. Specifically, each CN layer has $t$ groups of normalization parameters for $t$ hidden feature maps from samples generated by $t$ data transformation techniques, so that discrepancy between these feature maps can be reserved.

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The contributions of this work are as follows.

- We identify the inconsistency between BN and various data augmentation methods, such as scaling, blurring, and random cropping, showing that BN trained with data augmentation may result in a common and undesirable phenomenon, which is poor performance in many challenging tasks including image classification, and semantic image segmentation.

- To alleviate inconsistency between BN and data augmentation, we propose a novel normalization technique, Consistent Normalization (CN), which normalizes different hidden activations from different data augmentation approaches.

- We systematically compare CN and the plain normalization layers by implementing multiple data augmentation methods, and show that CN outperforms plain normalization layers, consisting of batch normalization and layer normalization, in various benchmarks and tasks including object classification, semantic scene parsing, and machine translation.

2 Related Work

Normalization. In addition to normalizing input data before the first layer, many normalization methods adjust the internal activations of one DNN have been proposed. Batch normalization (BN)\[8\] is a widely used ingredient that can normalize internal activations with statistics of training examples. After BN, several variants of LN are proposed. Layer normalization (LN)\[9\] can normalize activations using channel-wise statistics rather than the whole batch, which is popular in sequential models due to its less dependence on the batch size. Instance Normalization (IN)\[18\], on the other hand, normalizes each sample independently. Group normalization (GN)\[19\], which divides channels into several groups and normalizes each group independently for each sample, stabilizes training procedure when batch size is too small.

To better leverage the strength of each of these normalization methods, AdaBN\[10\], which re-estimates the statistics of each BN layer for the target domain, is proposed for transfer learning. Conditional BN\[4\] predicts corresponding weights and biases for each sample, whereas Switchable Normalization (SN)\[11,16\] normalizes data by combining IN, BN, and LN.

Data Augmentation. One of the best ways to improve the generalization and to reduce over-fitting of a DNN is to inject more data to the training set. Aside from gathering more instances from the wild that are representative of distinction tasks, data augmentation is developed to enhance the data we have collected. Cutout\[6\], for example, masks a square area from original input data for training, and Mixup\[22\] mixes both input images and their labels to train a more robust network.
3 Does normalization method always work well?

In this section, we will elaborate on the potential disadvantages brought by normalization methods to neural networks. Although normalization methods’ effectiveness is well-known, few studies emphasize on the limitation of a normalization layer. In this work, we first design the following experiments to try to explore on the possible disadvantages brought by ordinary normalization techniques.

We firstly augment CIFAR-10 dataset with a data transformation that scales the original images $x$ of size $32 \times 32$ into $x^t$, which are in the shape of $16 \times 16$. Then we pad the transformed $x^t$ with zero, matching the size of the $x$. The original image and augmented image is shown in Figure 2. We evaluate neural networks with batch normalization and without batch normalization both on original CIFAR-10 dataset and the augmented CIFAR-10 dataset, respectively. Specifically, the networks without batch normalization are modified (by adding bias parameters) and initialized as in [23]. In total, we have four independent experiments that are as follows:

(a) ResNet without batch normalization and without extra data transformation;
(b) ResNet with batch normalization and without extra data transformation;
(c) ResNet without batch normalization and with extra data transformation;
(d) ResNet with batch normalization and with extra data transformation.

For simplicity, we denote models with batch normalization as Conv-BN models and ones without batch normalization Conv-only models.

It is naturally expected that a Conv-BN model would perform better than a Conv-only model, which is coherent with previous research [15] [8]. Astoundingly, with the aggressive data transformations stated above, Conv-only model significantly outperforms Conv-BN model as shown in Figure 1 and Table 1. The main reason is that the convolutional layers in the Conv-BN model expect input of a normal Gaussian distribution while the Conv-only model does not hold any assumptions. We speculate that the effectiveness of the normalization layer may conceal its limitation in supervised learning. Inspired by these pilot experiments, we propose a novel hybrid framework to improve neural networks’ generalization by combining data transformations and normalization techniques consistently. (Details in Section 4.)

4 Training Neural Networks with Consistent Normalization

In this section, We first sketch the formulations of general normalization methods, then present CN. Under a supervised learning, our goal is to learn a predictive function $f : \mathcal{X} \rightarrow \mathcal{Y}$ that best describes the relationship between input $x \in \mathcal{X}$ and class label $y \in \mathcal{Y}$, and enables inference on previously unseen data $\hat{x} \in \mathcal{X}$. The discriminant function $f(\cdot)$, in our case the deep neural network, is optimized with what we so called the training data $D = \{(x_i, y_i)\}_{i=1}^N$, by minimizing the training discrepancy loss $\ell = \sum_{i=1}^N \mathcal{L}(f(x_i), y_i)$ between predicted label $\hat{y} = f(\hat{x})$ and the real label $y$. Here, $\mathcal{L}(\cdot)$ denotes the loss function.

4.1 Batch Normalization, Layer Normalization, and other seemingly "free" lunch

We now analyze neural network models with normalizations. We first describe a general formulation of a normalization layer. Let $h$ be some mini-batched input data of an arbitrary normalization layer,
When training a DNN by using original data, \( x \) would be better regarded as in a mixed Gaussian distribution instead of distributed under a simple Gaussian. In that case, normalizing \( x \) normalized into a standard Gaussian distribution is that convolution layers would receive more stable input. The premise for hidden feature maps is in a Gaussian distribution. However, under many circumstances, this premise does not stand.

Different normalization methods, such as BN, LN, IN, although share the same normalization formulation as Equation 1 shows, they have distinct mechanisms to estimate \( \mu \) and \( \sigma \). For example, BN estimates \( \mu \) and \( \sigma \) in the channel dimension, by which the incoming data pixels are normalized accordingly. LN, on the other hand, would estimated \( \mu \) and \( \sigma \) for each sample independently and normalize each pixel by the statistics of corresponding sample over all the hidden units in the same layer. IN normalizes input features just as BN does, but with independently estimated statistics for each sample. Other normalizations make estimations on \( \mu \) and \( \sigma \) similarly.

Although different normalization methods above have different formulations, they play a similar role: to preserve model expressiveness, whilst regularizing DNN training by transforming the feature map \( h \) into a standard Gaussian distribution so that the succeeding components of the network such as convolution layers would receive more stable input. The premise for hidden feature maps \( h \) to be normalized into a standard Gaussian distribution is that \( h \) is in a Gaussian distribution. However, under many circumstances, this premise does not stand.

When training a DNN by using original data \( x_n \) combined with some sort of augmented data \( x'_n \), which is, for example, generated by scaling input images from original data, the mixed training data would be better regarded as in a mixed Gaussian distribution instead of distributed under a simple Gaussian. In that case, normalizing \( x_n \) and \( x'_n \) as a whole may not work so well. This claim is further supported by our empirical evidence in Section 3.

### 4.2 Consistent Normalization

To tackle the potential problems resulted from the discrepancy between the distribution of \( \{x_n\} \) and \( \{x'_n\} \), we propose Consistent Normalization (CN). CN is perfectly compatible with any kind of normalization layer, as it switches the parameters according to current input, hence making the distributions of the input more desirable and the DNN parameters more stable. To better formulate this problem, we define a mini-batch of samples and the corresponding labels as \( \mathcal{X}_b = \{x_i\}_{i=1}^{N_b} \) and \( \mathcal{Y}_b = \{y_i\}_{i=1}^{N_b} \) respectively, where \( N_b \) denotes the size of the mini-batch \( \mathcal{X}_b \). Denote \( T = \{T_1, T_2, \ldots, T_t\} \) as a group of data transformation methods. Let \( \mathcal{X}_b^{(k)} = T_k(\mathcal{X}_b) = \{T_k(x_i)\}_{i=1}^{N_b} \) represent the mini-batch of samples \( \mathcal{X} \) transformed with some data transformation methods \( T_k \in T \), then a forward pass in the training phase can be described as

\[
\mathcal{X}_b \xrightarrow{T} \{\mathcal{X}_b^{(k)}\}_{k=1}^{t} \rightarrow \cdots \xrightarrow{W_i} \{\mathcal{Z}_b^{(k)}\}_{k=1}^{t} \xrightarrow{[\mu^{(k)}, \sigma^{(k)}, \gamma^{(k)}, \beta^{(k)}]} \{\hat{\mathcal{Z}}_b^{(k)}\}_{k=1}^{t} \xrightarrow{\lambda_k \mathcal{L}(\hat{\mathcal{Y}}_b^{(k)}, \mathcal{Y}_b)}
\]

where \( W_i \) represents \( i \)-th convolution layer parameters, \( \mathcal{Z}_b^{(k)} = \{z_i^{(k)}\}_{i=1}^{N_b} \) represents the output of the convolution layer for the mini-batch of samples transformed by \( T_k \). \( \{\hat{\mathcal{Z}}_b^{(k)}\}_{k=1}^{t} \) indicates the output of consistent normalization, and is formulated as \( \hat{\mathcal{Z}}_b^{(k)} = \left\{\gamma^{(k)} \frac{z_i^{(k)} - \mu^{(k)}}{\sqrt{(\sigma^{(k)})^2 + \epsilon}} + \beta^{(k)}\right\}_{i=1}^{N_b} \). During training phrase, for ordinary normalization methods (Equation 1), all input \( \{\mathcal{Z}_b^{(k)}\}_{k=1}^{t} \) share the same normalization parameters \( (\mu, \sigma, \gamma, \beta) \). Consistent normalization (CN), however, has one particular set of normalization parameters \( (\mu^{(k)}, \sigma^{(k)}, \gamma^{(k)}, \beta^{(k)}) \) for each \( \mathcal{Z}_b^{(k)} \), so that every \( \mathcal{Z}_b^{(k)} \) can be represented by a 4-dimensional tensor in the shape of \( (N, C, H, W) \), each indicates the number of samples, the number of channels, height and width of a channel, respectively. Traditionally, the normalized output can be computed as

\[
\hat{h}_{n,c,i,j} = \gamma \frac{h_{n,c,i,j} - \mu}{\sqrt{\sigma^2 + \epsilon}} + \beta, \quad (1)
\]

where \( \mu \) and \( \sigma \) are the standard and deviation of the mini-batch, while \( \gamma \) and \( \beta \) are the scale and shift parameters, respectively. Finally, \( \epsilon \) is a small constant to preserve numerical stability.

Note that \( T \) must consist of the identity transform \( T_1 \), in which \( T_1(x) = x \) for any sample \( x \). For example, \( T = \{\text{identity transform, scaling_to_size1, scaling_to_size2, noising, cutout}\} \).
independently normalized into \( \{ \hat{Z}_b^{(k)} \}_{k=1}^t \) which help release the power of data augmentation for subsequent layers.

The inference phase for DNNs with CN is the same as that of DNNs with ordinary normalization, the consistent normalization does not introduce any extra expense of memory or computation during inference, since we only preserve normalization parameters corresponding to data via identity transformation.

The detailed training process when utilizing CN is described in Algorithm 1.

**Algorithm 1 Training phase with Consistent Normalizations**

**Require:** Input transformations \( T = \{T_i\}_{i=1}^t \), initialized DNN model \( M \), loss factors \( \{\lambda_i\}_{i=1}^t \)

1: for \( j = 1, ..., n_{\text{iters}} \) do
2: Randomly sample a mini-batch of data \( \mathcal{X}_b = \{x_i\}_{i=1}^{N_b} \) and label \( \mathcal{Y}_b = \{y_i\}_{i=1}^{N_b} \)
3: loss \( \leftarrow 0 \)
4: for \( T_k \in T \) do
5: \( \mathcal{X}_b^{(k)} \leftarrow T_k(\mathcal{X}_b) \)
6: // Replace the parameters of each normalization layer with the ones corresponding to data transformation \( T_i \) to keep consistent with input transformation
7: \( M.\text{assign}(k) \)
8: \( \hat{\mathcal{Y}}_b^{(k)} \leftarrow M(\mathcal{X}_b^{(k)}) \)
9: loss \( \leftarrow \) loss + \( \lambda_k \mathcal{L}(\hat{\mathcal{Y}}_b^{(k)}, \mathcal{Y}_b) \)
10: optimize \( M \) with loss

5 Experiments

We set \( \lambda_k = 1 \) for each data transformation in the following experiments. All models are trained with 8 NVIDIA V100 GPUs.

5.1 Image Classification

For image classification tasks, we evaluate CN on CIFAR-10, CIFAR-100, and ImageNet datasets with several data augmentation techniques including scaling, noising. Our neural networks are based on the architecture of ResNet-18 and ResNet-50. To compare BN and CN, we simply replace batch normalization layers with consistent normalization layers.

5.1.1 Back to the pilot experiment in Section 3

In Section 3, we compared Conv-only models and Conv-BN models with an augmented CIFAR-10 dataset as described before, and pointed out the potential shortcomings BN brings to neural networks. We now evaluate CN under the same setting as in Section 3. Clearly, as Table I shows, CN is totally compatible with the augmented dataset, and achieves much better performance than BN does. In Table I, “CIFAR-10-a” stands for the CIFAR-10 dataset augmented with padding and scaling. These networks are trained for 250 epochs using batch size 128, during which the learning rate starts from 0.1 and is divided by 10 at 100, 150 and 200 epochs.

Visualizations. We visualize the distributions of features maps after the first residual block of ResNet-32 without BN, ResNet-32 with BN, and ResNet-32 with CN. We evaluate our trained neural networks with CIFAR-10-a evaluation set, which is CIFAR-10 augmented by using resizing and padding. As Figure 3a shows, when CIFAR-10 is evaluated on ResNet-32 with BN, the distributions of the feature maps for original data and those for augmented data are normalized into nearly the same distribution. However, for the other two networks, ResNet-32 without BN and ResNet-32 with CN, the distributions of these two feature maps share fewer similarities (Figure 3b and Figure 3c).

We believe the significant drop of performance of ResNet-32 with BN on CIFAR-10-a is resulted by combining two different sets of feature maps together with only one set of parameters \( \{\mu, \sigma, \gamma, \beta\} \). On the other hand, CN instead of BN, networks can reserve the special traits for different sets of hidden feature maps to aid the training process.
### Table 1: Validation accuracy for CIFAR-10 and augmented CIFAR-10 (CIFAR-10-a)

| Model   | Dataset | Method  | Top-1 Acc | Top-1 Acc Gain |
|---------|---------|---------|-----------|----------------|
| ResNet-32 | CIFAR-10 | with BN | 92.9      | -              |
|         |         | w/o BN  | 92.1      | -0.8           |
|         | CIFAR-10-a | with BN | 89.7      | -3.2           |
|         |         | w/o BN  | 92.6      | -0.3           |
|         |         | with CN | 93.3      | 0.4            |
| ResNet-110 | CIFAR-10 | with BN | 94.0      | -              |
|         |         | w/o BN  | 93.6      | -0.4           |
|         | CIFAR-10-a | with BN | 92.3      | -1.7           |
|         |         | w/o BN  | 94.0      | 0.0            |
|         |         | with CN | 94.6      | 0.6            |

![Figure 3: Visualizations of feature maps after the first residual block of ResNet-32 on CIFAR-10-a](image)

5.1.2 Scaling

The ordinary shape of input images for training DNNs on ImageNet is $224 \times 224$ (width \times height). We scale images with the size of $224 \times 224$ into samples of other sizes such as $192 \times 192$, $160 \times 160$, $320 \times 320$, which are combined to form the augmented training set. In the evaluation phase, the $224\times224$ central crop of each image is tested.

**Experiment setup.** To evaluate our method’s effectiveness, we pick up strong baselines when training ResNet model on ImageNet, we use warm-up trick for the first 5 epochs and anneal the learning rate from 0.1 to 0 with a cosine scheduler\cite{20}. The number epochs of training is set to 120 and the batch size is 256.

Comparisons between the performance of BN and CN. As Table 2 shows, BN brings limited performance gain compared to CN on both shallower (ResNet-18) and deeper (ResNet-50) neural networks. Moreover, these performance gains have nothing to do with the number of parameters since in the inference phase because for every CN layer, only the parameters of the corresponding input image size are utilized. In other words, CN neither adds computation cost nor increases model capacity.

5.1.3 Other data augmentation methods

To further investigate on the adaptability of CN to other data transformation methodologies, we evaluate ResNet-18 on ImageNet dataset augmented by blurring and random cropping respectively.

**Experiment Settings.** In this experiment, ResNet-18 networks are trained under the same settings as in 5.1.2. To blur input data, we create a Gaussian filter using a convolution layer. As for random cropping, we choose one number from $[32, 64, 96, 128, 160, 192, 224]$ with a medium probability for each mini-batch as the size of the cropped regions, and then randomly select one pixel as the top-left pixel of the cropped region for each image in that mini-batch.

**Comparisons.** Results are shown in Table 3. For ResNet-18 with BN, both the blurred images and randomly cropped images are not helping as expected, on the contrary, as the top-1 accuracy
Table 2: Validation accuracy for BN and CN on the validation set of ImageNet (ILSVRC-2012).

| Model   | Method | Input sizes | Top-1 Acc | Top-5 Acc | Top-1 Acc gain |
|---------|--------|-------------|-----------|-----------|----------------|
| ResNet-18 | BN     | 224         | 71.1      | 90.0      |                |
|         | BN     | 224, 192, 128 | 71.9      | 90.5      | 0.8            |
|         | CN     | 224, 192, 128 | 72.8      | 91.0      | 1.7            |
|         | CN     | 320, 224, 192, 128 | 73.2      | 91.2      | 2.1            |
| ResNet-50 | BN     | 224         | 77.1      | 93.3      |                |
|         | BN     | 224, 192, 128 | 77.3      | 93.4      | 0.2            |
|         | CN     | 224, 192, 128 | 78.3      | 94.1      | 1.2            |
|         | CN     | 320, 224, 192, 128 | 78.8      | 94.5      | 1.7            |

Ablation study

5.1.4 Ablation study

Training loss. When training neural networks with extra data transformations, the training loss equals to the sum of training losses for every transformed batch of samples since we set $\lambda_t = 1$ for every transformation method, which approximately multiply the training loss by the number of transformations $t$ compared to training without extra data transformations. To make sure the performance gain does not only result from the increased loss, we evaluate ResNet-18 on ImageNet with a training loss as 3 times much as before. As Table 4 shows, training ResNet-18-BN with 3 times loss have no performance gain compared with training under regular settings.

Table 3: Validation accuracy on ImageNet validation set for the transformation of blurring and random-cropping

| Model   | Method | Augmentation | Top-1 Acc | Top-5 Acc | Top-1 Acc Gain |
|---------|--------|--------------|-----------|-----------|----------------|
| ResNet-18 | BN     | -            | 71.1      | 90.0      |                |
|         | BN     | blurring     | 70.0      | 89.4      | -1.1           |
|         | CN     | blurring     | 71.1      | 90.0      | +0.0           |
|         | BN     | cropping     | 69.2      | 88.9      | -1.9           |
|         | CN     | cropping     | 71.2      | 90.0      | +0.1           |

Results on images of other sizes. Although we care most about the performance on the original dataset, if we evaluate the network with images of other sizes instead of 224 × 224, such as 192 × 192 and 128 × 128, we still observe obvious performance gains, as shown in Table 5. Therefore, this framework can perform dynamic inference on devices with different resource budgets by adopting different input scale. With CN, neural networks can outperform [21] with similar FLOPS if they are trained and evaluated with multiple input image sizes.

5.2 Semantic Scene Parsing

We compare CN and BN further in semantic segmentation on the Cityscapes dataset[3].
Table 5: Validation errors on images of ImageNet (ILSVRC-2012) in other sizes for BN and CN.

| Model   | Method | Input Sizes | Top-1 Acc (192) | Top-1 Acc (128) |
|---------|--------|-------------|-----------------|-----------------|
| ResNet-18 | BN     | 224,192,128 | 71.1            | 65.0            |
|         | CN     | 224,192,128 | 71.4            | 65.8            |
|         | CN     | 320,224,192,128,96 | 71.9            | 66.8            |
| ResNet-50 | BN     | 224,192,128 | 75.9            | 70.5            |
|         | CN     | 224,192,128 | 76.8            | 73.0            |
|         | CN     | 320,224,192,128,96 | 77.7            | 73.9            |

**Experiment Setup:** For semantic segmentation on Cityscapes (2975 samples for training and 500 for testing), we augment the Cityscapes dataset with the partial GTA5\[14\] dataset (same number of samples as Cityscapes), then evaluate DeepLab with BN and CN on these two datasets together. We utilize DeepLab\[2\] with ResNet-50 as our backbone network, where output stride = 8 and the last two blocks in the backbone contains atrous convolution with rate = 2 and rate = 4 respectively. Following\[24\], we employ “poly” learning rate policy with power = 0.9 and use the auxiliary loss with the weight 0.4 during training.

**Comparisons between BN and CN.** Our results are elaborated in Table 6 in which the network receives significant performance drops as GTA5 dataset is added. When CN the ingredient is added to the network, however, we receive notable improvement on some classes such as wall (+2.1), fence (+4.3), truck (+4.2), mbike (+5.5). One thing that is common among these classes is that the ratios of pixels of these classes in Cityscapes are relatively small. We believe it is the pixels of those classes in GTA5 that help training the network as auxiliary resources.

Table 6: mIoU results on Cityscapes validation set for different classes.

| Method | Augm. | road | swalk | build. | wall | fence | pole | tli. | sign | veg. | ter. |
|--------|-------|------|-------|--------|------|-------|------|------|------|------|------|
| BN     | -     | 98.5 | 74.6  | 89.1   | 42.8 | 42.0  | 46.3 | 62.4 | 71.1 | 91.2 | 53.2 |
| BN     | GTAV  | 97.9 | 66.0  | 86.2   | 36.8 | 30.4  | 39.4 | 56.6 | 62.0 | 89.4 | 42.5 |
| CN     | GTAV  | 98.5 | 75.1  | 89.4   | 44.9 | 46.3  | 46.2 | 63.0 | 70.9 | 91.3 | 54.0 |

| Method | Augm. | sky | pers. | rider | car | truck | bus | tra. | mbike | bike | mIoU |
|--------|-------|-----|-------|-------|-----|-------|-----|------|-------|------|------|
| BN     | -     | 91.8 | 80.3  | 60.9  | 91.6 | 69.2  | 81.2 | 67.1 | 56.7  | 71.9 | 69.8 |
| BN     | GTAV  | 90.0 | 76.3  | 56.3  | 90.3 | 63.3  | 74.0 | 40.1 | 54.2  | 65.3 | 60.9 |
| CN     | GTAV  | 91.9 | 80.9  | 61.4  | 92.2 | 73.4  | 82.7 | 68.3 | 63.2  | 71.6 | 70.7 |

5.3 Machine Translation

In order to evaluate the expandability of CN, we employ CN instead of standard LC on the standard machine translation dataset, i.e., WMT English-German. We augment the input length by half and one and a half. Our implement is based on fairseq\[12\] library and we adopt the experimental setting in Ott et.al\[13\]. All models are trained for 200k updates with a dropout rate of 0.4. Results are shown in Table 7.

| Dataset   | Model          | Method | BLEU |
|-----------|----------------|--------|------|
| WMT EN-DE | LayerNorm(Ott et al., 2018) | LN     | 29.3 |
|           | CN + Transformer | CN     | **29.4** |

6 Conclusions

To our knowledge, we are the first to identify the inconsistency between data augmentations and normalization methods. To tackle the inconsistency, we propose Consistent Normalization for training.
neural networks with extra data transformations. Our proposed method provide a brand-new training framework for DNNs that utilizes the traits of different augmented samples efficiently and reconciles layers in a deep network and different distributions of data from different data transformations. We hope that these findings not only change the conventional wisdom about normalization methods but also shed light on the understanding of neural networks.

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