On Feature Normalization and Data Augmentation

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Abstract
Modern neural network training relies heavily on data augmentation for improved generalization. After the initial success of label-preserving augmentations, there has been a recent surge of interest in label-perturbing approaches, which combine features and labels across training samples to smooth the learned decision surface. In this paper, we propose a new augmentation method that leverages the first and second moments extracted and re-injected by feature normalization. We replace the moments of the learned features of one training image by those of another, and also interpolate the target labels. As our approach is fast, operates entirely in feature space, and mixes different signals than prior methods, one can effectively combine it with existing augmentation methods. We demonstrate its efficacy across benchmark data sets in computer vision, speech, and natural language processing, where it consistently improves the generalization performance of highly competitive baseline networks.

1. Introduction
Deep learning has had a dramatic impact across many fields, including computer vision, automated speech recognition (ASR), and natural language processing (NLP). Fueled by these successes, significant effort has gone into the search for ever more powerful and bigger neural network architectures (Krizhevsky et al., 2012; He et al., 2015; Zoph & Le, 2016; Huang et al., 2019; Vaswani et al., 2017). These innovations, along with progress in computing hardware, have enabled researchers to train enormous models with billions of parameters (Radford et al., 2019; Keskar et al., 2019; Raffel et al., 2019). Such over-parameterized models can easily memorize the whole training set even with random labels (Zhang et al., 2017). To address overfitting, neural networks are trained with heavy regularization, which can be explicit, for example in the case of data augmentation (Simard et al., 1993; Frühwirth-Schnatter, 1994; Schölkopf et al., 1996; Van Dyk & Meng, 2001) and dropout (Srivastava et al., 2014), or implicit, such as early stopping and intrinsic normalization (Ioffe & Szegedy, 2015; Ba et al., 2016).

The most common form of data augmentation is based on label-preserving transformations. For instance, practitioners (Simard et al., 1993; Krizhevsky et al., 2012; Szegedy et al., 2016) randomly flip, crop, translate, or rotate images — assuming that none of these transformations alter their class memberships. Chapelle et al. (2001) formalizes such transformations under the Vicinal Risk Minimization (VRM) principle, where the augmented data sampled within the vicinity of an observed instance are assumed to have the same label. Zhang et al. (2018) takes it a step further and introduce Mixup, a label-perturbing data augmentation method where two inputs and their corresponding labels are linearly interpolated to smooth out the decision surface between them. As a variant, Yun et al. (2019) cuts and pastes a rectangular patch from one image into another and interpolate the labels proportional to the area of the patch.

A key ingredient to optimizing such deep neural networks is Batch Normalization (Ioffe & Szegedy, 2015; Zhang et al., 2017). A series of recent studies (Björck et al., 2018; Santurkar et al., 2018) show that normalization methods change the loss surface and lead to faster convergence by enabling larger learning rates in practice. While batch normalization has arguably contributed substantially to the deep learning revolution in visual object recognition, its performance degrades on tasks with smaller mini-batch or variable input sizes (e.g. many NLP tasks). This has motivated the quest to find normalization methods for single instances, such as LayerNorm (LN) (Ba et al., 2016), InstanceNorm (IN) (Ulyanov et al., 2016), GroupNorm (GN) (Wu & He, 2018), and recently PositionalNorm (PONO) (Li et al., 2019). These intra-instance normalizations treat each example as a distribution and normalize them with respect to their first and second moments — essentially removing the moment information from the feature representation and re-learning them through scaling and offset constants.

Up to this point, data augmentation was considered more or less independent of the normalization method used during training. In this paper, we introduce a novel label-perturbing...
data augmentation approach that integrates naturally with feature normalization. It has been argued previously, that the first and second moments extracted in intra-instance normalization capture the underlying structure of an image (Li et al., 2019). We propose to extract these moments, but instead of simply removing them, we re-inject moments from a different image and interpolate the labels — for example, injecting the structure of a plane into the image of a cat to obtain a mixture between cat and plane. See Fig. 1 for a schematic illustration. In practice, this procedure is very effective for training with mini-batches and can be implemented in a few lines of code: During training we compute the feature mean and variance for each instance at a given layer, permute them across the mini-batch, and re-inject them into the feature representation of other instances (while interpolating the labels). In other words, we randomly exchange the feature moments across samples, and we therefore refer to our method as Moment Exchange (MoEx).

Unlike previous methods, MoEx operates purely in feature space and can therefore easily be applied jointly with existing data augmentation methods that operate in the input space, such as cropping, flipping, rotating, but even label-perturbing approaches like Cutmix or Mixup. We refer to the extracted mean and variance as intra-instance moments. We argue that intra-instance moments are attributes of a data instance that describe the distribution of its features and should not be discarded. Recent works (Huang & Belongie, 2017; Li et al., 2019) have shown that such attributes can be useful in several generative models. Re-alizing that these moments capture interesting information about data instances, we propose to use them for data augmentation.

We conduct extensive experiments on eleven different tasks/datasets using more than ten varieties of models. The results show that MoEx consistently leads to significant improvements across models and tasks, and it is particularly well suited to be combined with existing augmentation approaches. Further, our experiments show that MoEx is not limited to computer vision, but is also readily applicable and highly effective in applications within speech recognition and NLP. The code for MoEx is available at https://github.com/Boyiliiee/MoEx.

2. Background and Related Work

Feature normalization has always been a prominent part of neural network training (LeCun et al., 1998; Li & Zhang, 1998). Initially, when networks had predominately one or two hidden layers, the practice of z-scoring the features was limited to the input itself. As networks became deeper, Ioffe & Szegedy (2015) extended the practice to the intermediate layers with the celebrated BatchNorm algorithm. As long as the mean and variance are computed across the entire input, or a randomly picked mini-batch (as it is the case for BatchNorm), the extracted moments reveal biases in the data set with no predictive information — removing them causes no harm but can substantially improve optimization and generalization (LeCun et al., 1998; Bjorck et al., 2018; Ross et al., 2013).

In contrast, recently proposed normalization methods (Ba et al., 2016; Ulyanov et al., 2016; Wu & He, 2018; Li et al., 2019) treat the features of each training instance as a distribution and normalize them for each sample individually. Unlike previous methods, MoEx operates purely in feature space and can therefore easily be applied jointly with existing data augmentation methods that operate in the input space, such as cropping, flipping, rotating, but even label-perturbing approaches like Cutmix or Mixup. Importantly, because MoEx only alters the first and second moments of the pixel distributions, it has an orthogonal effect to existing data augmentation methods and its improvements can be “stacked” on top of their established gains in generalization.

Data augmentation has a similarly long and rich history in machine learning. Initial approaches discovered the concept of label-preserving transformations (Simard et al., 1993; Schölkopf et al., 1996) to mimic larger training data sets to suppress overfitting effects and improve generalization. For instance, Simard et al. (2003) randomly translates or rotates images assuming that the labels of the images would not change under such small perturbations. Many subsequent papers proposed alternative flavors of this augmentation approach based on similar insights (DeVries & Taylor, 2017;
Kawaguchi et al., 2018; Cubuk et al., 2019a; Zhong et al., 2020; Karras et al., 2019; Cubuk et al., 2019b; Xie et al., 2019; Singh & Lee, 2017). Beyond vision tasks, back-translation (Sennrich et al., 2015; Yu et al., 2018; Edunov et al., 2018a; Caswell et al., 2019) and word dropout (Iyyer et al., 2015) are commonly used to augment text data. Besides augmenting inputs, Maaten et al. (2013); Ghiasi et al. (2018); Wang et al. (2019) adjust either the features or loss function as implicit data augmentation methods. In addition to label-preserving transformations, there is an increasing trend to use label-perturbing data augmentation methods. Zhang et al. (2018) arguably pioneered the field with Mixup, which interpolates two training inputs in feature and label space simultaneously. Cutmix (Yun et al., 2019), instead, is designed especially for image inputs. It randomly crops a rectangular region of an image and pastes it into another image, mixing the labels proportional to the number of pixels contributed by each input image to the final composition.

3. Moment Exchange

In this section we introduce Moment Exchange (MoEx), which blends feature normalization with data augmentation. Similar to Mixup and Cutmix, it fuses features and labels across two training samples, however it is unique in its asymmetry, as it mixes two very different components: the normalized features of one instance are combined with the feature moments of another. This asymmetric composition in feature space allows us to capture and smooth out different directions of the decision boundary, not previously covered by existing augmentation approaches. We also show that MoEx can be implemented very efficiently in a few lines of code, and should be regarded as a cheap and effective companion to existing data augmentation methods.

Setup. Deep neural networks are composed of layers of transformations including convolution, pooling, transformers (Vaswani et al., 2017), fully connected layers, and non-linear activation layers. Consider a batch of input instances \( x \), these transformations are applied sequentially to generate a series of hidden features \( h^1, ..., h^\ell \) before passing the final feature \( h^\ell \) to a linear classifier. For each instance, any feature presentation \( h^\ell \) is a three dimensional vector indexed by channel (C), height (H), and width (W).

Normalization. We assume the network is using an invertible intra-instance normalization method. Let us denote this function by \( F \), which takes the features \( h^i \) of the \( i \)-th input \( x_i \) at layer \( \ell \) and produces three outputs, the normalized features \( \hat{h}_i \), the first moment \( \mu_i \), and the second moment \( \sigma_i \):

\[
(\hat{h}_i^\ell, \mu_i^\ell, \sigma_i^\ell) = F(h_i^\ell), \quad h_i^\ell = F^{-1}(\hat{h}_i^\ell, \mu_i^\ell, \sigma_i^\ell).
\]

The inverse function \( F^{-1} \) reverses the normalization process. As an example, PONO (Li et al., 2019) computes the first and second moments across channels from the feature representation at a given layer

\[
\mu_{b,h,w}^\ell = \frac{1}{C} \sum_c h_{b,c,h,w}^\ell,
\]

\[
\sigma_{b,h,w}^\ell = \sqrt{\frac{1}{C} \sum_c \left(h_{b,c,h,w}^\ell - \mu_{b,h,w}^\ell\right)^2} + \epsilon.
\]

The normalized features have zero-mean and standard deviation 1 along the channel dimension. Note that other inter-instance normalizations, such as batch-norm, can also be used in addition to the intra-instance normalization \( F \), with their well-known beneficial impact on convergence. As the norms compute statistics across different dimensions their interference is insignificant.

Moment Exchange. The procedure described in the following functions identically for each layer it is applied to and we therefore drop the \( \ell \) superscript for notational simplicity. Further, for now, we only consider two randomly chosen samples \( x_A \) and \( x_B \) (see Fig. 1 for a schematic illustration). The intra-instance normalization decomposes the features of input \( x_A \) at layer \( \ell \) into three parts, \( \hat{h}_A, \mu_A, \sigma_A \). Traditionally, batch-normalization (Ioffe & Szegedy, 2015) discards the two moments and only proceeds with the normalized features \( \hat{h}_A \). If the moments are computed across instances (e.g. over the mini-batch) this makes sense, as they capture biases that are independent of the label. However, in our case we focus on intra-instance normalization, and therefore both moments are computed only from \( x_A \) and are thus likely to contain label-relevant signal. This is clearly visible in the cat and plane examples in Figure 1. All four moments \( (\mu_A, \sigma_A, \mu_B, \sigma_B) \), capture the underlying structure of the samples, distinctly revealing their respective class labels.

We consider the normalized features and the moments as distinct views of the same instance. It generally helps robustness if a machine learning algorithm leverages multiple sources of signal, as it becomes more resilient in case one of them is under-expressed in a test example. For instance, the first moment conveys primarily structural information and only little color information, which, in the case of cat images can help overcome overfitting towards fur color biases in the training data set.

In order to encourage the network to utilize the moments, we use the two images and combine them by injecting the moments of image \( x_B \) into the feature representation of image \( x_A \):

\[
h_A^{(B)} = F^{-1}(\hat{h}_A, \mu_A, \sigma_B)
\]
In the case of PONO, the transformation becomes
\[ h_A^{(B)} = \sigma_B \frac{h_A - \mu_A}{\sigma_A} + \mu_B. \] (2)

We now proceed with these features \( h_A^{(B)} \), which contain the moments of image B (plane) hidden inside the features of image A (cat). In order to encourage the neural network to pay attention to the injected features of B we modify the loss function to predict the class label \( y_A \) and also \( y_B \), up to some mixing constant \( \lambda \in [0, 1] \). The loss becomes a straight-forward combination
\[ \lambda \cdot \ell(h_A^{(B)} , y_A) + (1 - \lambda) \cdot \ell(h_B^{(B)} , y_B). \]

**Implementation.** In practice one needs to apply MoEx only on a single layer in the neural network, as the fused signal is propagated until the end. With PONO as the normalization method, we observe that the first layer (\( \ell = 1 \)) usually leads to the best result. In contrast, we find that MoEx is more suited for later layers when using IN (Ulyanov et al., 2016), GN (Wu & He, 2018), or LN (Ba et al., 2016) for moment extraction. Please see Subsec. 5.1 for a detailed ablation study. The inherent randomness of mini-batches allows us to implement MoEx very efficiently. For each input instance in the mini-batch \( x_i \), we compute the normalized features and moments \( h_i, \mu_i, \sigma_i \). Subsequently we sample a random permutation \( \pi \) and apply MoEx with a random pair within the mini-batch
\[ h_i^{(\pi(i))} \rightarrow F^{-1}(h_{\pi(i)}, \mu_{\pi(i)}, \sigma_{\pi(i)}). \] (3)

See Algorithm 1 in the Appendix for an example implementation in PyTorch (Paszke et al., 2017). Note that all computations are extremely fast and only introduce negligible overhead during training.

**Hyper-parameters.** To control the intensity of our data augmentation, we perform MoEx during training with some probability \( p \). In this way, the model can still see the original features with probability \( 1 - p \). In practice we found that \( p = 0.5 \) works well on most datasets except that we set \( p = 1 \) for ImageNet where we need stronger data augmentation. The interpolation weight \( \lambda \) is another hyper-parameter to be tuned. Empirically, we find that 0.9 works well across data sets. The reason can be that the moments contain less information than the normalized features. Please see Subsec. 5.2 for a detailed ablation study.

**Properties.** MoEx is performed entirely at the feature level inside the neural network and can be readily combined with other augmentation methods that operate on the raw input (pixels or words). For instance, Cutmix Yun et al. (2019) typically works best when applied on the input pixels directly. We find that the improvements of MoEx are complimentary to such prior work and recommend to use MoEx in combination with established data augmentation methods.

| Model                  | #param. | CIFAR10 | CIFAR100 |
|------------------------|---------|---------|----------|
| ResNet-110 (3-stage)   | 1.7M    | 6.82±0.23 | 26.28±0.10 |
| +MoEx                  | 1.7M    | 6.03±0.24 | 25.47±0.09 |
| DenseNet-BC-100 (k=12) | 0.8M    | 4.67±0.10 | 22.61±0.17 |
| +MoEx                  | 0.8M    | 4.58±0.03 | 21.38±0.18 |
| ResNet-29 (8×64d)      | 34.4M   | 4.00±0.04 | 18.54±0.27 |
| +MoEx                  | 34.4M   | 3.64±0.07 | 17.08±0.12 |
| WRN-28-10              | 36.5M   | 3.85±0.06 | 18.67±0.07 |
| +MoEx                  | 36.5M   | 3.31±0.03 | 17.69±0.10 |
| DenseNet-BC-190 (k=40) | 25.6M   | 3.31±0.04 | 17.10±0.02 |
| +MoEx                  | 25.6M   | 2.87±0.03 | 16.09±0.14 |
| PyramidNet-200 (\( \alpha = 240 \)) | 26.8M | 3.65±0.10 | 16.51±0.05 |
| +MoEx                  | 26.8M   | 3.44±0.03 | 15.50±0.27 |

Table 1. Classification results (Err (%)) on CIFAR-10, CIFAR-100 in comparison with various competitive baseline models. WRN-28-10: Wide ResNet depth=28, widening parameter k=10 (dropout (Srivastava et al., 2014): 0.3), DenseNet-BC (L=100, k=12): depth L=100, growth rate k=12. Note: for these models, we follow the official github, we train ResNet110 for 164 epochs, WRN-28-10 for 200 epochs, others for 300 epochs.

4. Experiments

We evaluate the efficacy of our approach thoroughly across several tasks and data modalities. Our implementation will be released as open source upon publication.

4.1. Image Classification on CIFAR

**Setup.** CIFAR-10 and CIFAR-100 (Krizhevsky et al., 2009) are benchmark datasets containing 50K training and 10K test colored images at 32x32 resolution. We evaluate our method using various model architectures (He et al., 2015; Huang et al., 2017; Xie et al., 2017; Zagoruyko & Komodakis, 2016; Han et al., 2017) on CIFAR-10 and CIFAR-100. We follow the conventional setting\(^1\) with random translation as the default data augmentation and apply MoEx to the features after the first layer. Furthermore, to justify the compatibility of MoEx with other regularization methods, we follow the official setup\(^2\) of (Yun et al., 2019) and apply MoEx jointly with several regularization methods to PyramidNet-200 (Han et al., 2017) on CIFAR-100.

**Results.** Table 1 displays the classification results on CIFAR-10 and CIFAR-100 using MoEx or not. We take three random runs and report the mean and standard error (Gurland & Tripathi, 1971). MoEx consistently enhances the performance of all the baseline models.

Table 2 demonstrates the CIFAR-100 classification results on the basis of PyramidNet-200. Compared to other aug-

\(^1\)https://github.com/bearpaw/pytorch-classification
\(^2\)https://github.com/clovaai/CutMix-PyTorch
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| Model                        | # of epochs | Test Error (%) | Baseline  | +MoEx |
|------------------------------|-------------|----------------|-----------|-------|
| ResNet-50                    | 90          | 23.6           | 23.1      |       |
| ResNeXt-50 (32 × 4d)         | 90          | 22.2           | 21.4      |       |
| DenseNet-265                 | 90          | 21.9           | 21.6      |       |
| ResNet-50                    | 300         | 23.1           | 21.9      |       |
| ResNeXt-50 (32 × 4d)         | 300         | 22.5           | 22.0      |       |
| DenseNet-265                 | 300         | 21.5           | 20.9      |       |

Table 3. Classification results (Test Err (%)) on ImageNet in comparison with various models. Note: The ResNeXt-50 (32 × 4d) models trained for 300 epochs overfit. They have higher training accuracy but lower test accuracy than the 90-epoch ones.

MoEx is able to improve the classification performance throughout, regardless of model architecture. Similar to the previous CIFAR experiments, we observe in Table 4 that MoEx is highly competitive when compared to existing regularization methods and truly shines when it is combined with them. When applied jointly with CutMix (the strongest alternative), we obtain our lowest Top-1 and Top-5 error of 20.9/5.7 respectively. Due to computational limitations we only experimented with a ResNet-50, but expect similar trends for other architectures.

### 4.2. Image Classification on ImageNet

**Setup.** We evaluate on ImageNet (Deng et al., 2009) (ILSVRC 2012 version), which consists of 1.3M training images and 50K validation images of various resolutions. For faster convergence, we use NVIDIA’s mixed-precision training code base with batch size 1024, default learning rate 0.1 × batch_size / 256, cosine annealing learning rate scheduler (Loshchilov & Hutter, 2016) with linear warmup (Goyal et al., 2017) for the first 5 epochs. As the model might require more training updates to converge with data augmentation, we apply MoEx to ResNet-50, ResNetXt-50 (32 × 4d), DenseNet-265 and train them for 90 and 300 epochs. For a fair comparison, we also report Cutmix (Yun et al., 2019) under the same setting.

### Results.

Table 3 shows the test error rates on the ImageNet data set. MoEx is able to improve the classification performance throughout, regardless of model architecture. Similar to the previous CIFAR experiments, we observe in Table 4 that MoEx is highly competitive when compared to existing regularization methods and truly shines when it is combined with them. When applied jointly with CutMix (the strongest alternative), we obtain our lowest Top-1 and Top-5 error of 20.9/5.7 respectively. Due to computational limitations we only experimented with a ResNet-50, but expect similar trends for other architectures.

Beyond classification, we also finetune the pre-trained ImageNet models on Pascal VOC object detection task and find that weights pre-trained with MoEx provide a better initialization when finetuned on downstream tasks. Please see Appendix for details.

### 4.3. Speech Recognition on Speech Commands

**Setup.** To demonstrate that MoEx can be applied to speech models as well, we use Speech Command dataset (Warden, 2018) which contains 65000 utterances (one second long) from thousands of people. The goal is to classify them in

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1. https://github.com/NVIDIA/apex/tree/master/examples/imagenet
2. We attribute the Speech Command dataset to the Tensorflow team and AY project: https://ai.googleblog.com/2017/08/launching-speech-commands-dataset.html
to 30 command words such as "Go", "Stop", etc. There are 56196, 7477, and 6835 examples for training, validation, and test. We use an open source implementation\(^5\) to encode each audio into a mel-spectrogram of size 1x32x32 and feeds it to 2D ConvNets as an one-channel input. We follow the default setup in the codebase training models with initial learning rate 0.01 with ADAM (Kingma & Ba, 2014) for 70 epochs. The learning rate is reduce on plateau. We use the validation set for hyper-parameter selection and tune the hyper-parameters of MoEx on the validation set of the default setup in the codebase training models with initial learning rate 0.001. We tune the hyper-parameters of MoEx on three baselines models: DenseNet-BC-100, VGG-11-BN, and WRN-28-10.

**Results.** Table 5 displays the validation and test errors. We observe that training models with MoEx improve over the baselines significantly in all but one case. The only exception is DenseNet-BC-100, which has only 2% of the parameters of the wide resnet, confirming the findings of Zhang et al. (2018) that on this data set data augmentation has little effect on tiny models.

### 4.4.3D model classification on ModelNet

**Setup.** We conduct experiments on Princeton ModelNet10 and ModelNet40 datasets (Wu et al., 2015) for 3D model classification. This task aims to classify 3D models encoded as 3D point clouds into 10 or 40 categories. As a proof of concept, we use PointNet++ (SSG) (Qi et al., 2017) implemented efficiently in PyTorch Geometric\(^6\) (Fey & Lenssen, 2019) as the baseline. It does not use surface normal as additional inputs. We apply MoEx to the features after the first set abstraction layer in PointNet++. Following their default setting, all models are trained with ADAM (Kingma & Ba, 2014) at batch size 32 for 200 epochs. The learning rate is set to 0.001. We tune the hyper-parameters of MoEx on ModelNet-10 and apply the same hyper-parameters to ModelNet-40. We choose \(p = 0.5, \lambda = 0.9\), and InstanceNorm\(^7\) for this task, which leads to slightly better results.

\(^5\)https://github.com/tugstugi/pytorch-speech-commands
\(^6\)https://github.com/rusty1s/pytorch_geometric
\(^7\)We do hyper-parameter search from \(p \in \{0.5, 1\}, \lambda \in \{0.5, 0.9\}\) and whether to use PONO or InstanceNorm.

| Model          | # Param | Val Err | Test Err |
|----------------|---------|---------|----------|
| DenseNet-BC-100| 0.8M    | 3.16    | 3.23     |
| +MoEx          |         |         |          |
| VGG-11-BN      | 28.2M   | 3.05    | 3.38     |
| +MoEx          |         |         |          |
| WRN-28-10      | 36.5M   | 2.42    | 2.21     |
| +MoEx          |         |         |          |

Table 5. Speech classification on Speech Command. Similar to the observation of Zhang et al. (2018), regularization methods work better for models with large capacity on this dataset.

**Results.** Table 6 summarizes the results out of three runs, showing mean error rates with standard errors. MoEx reduces the classification errors from 6.0% to 5.3% and 9.2% to 8.8% on ModelNet10 and ModelNet40, respectively.

| Task | Method | BLEU ↑ | BERT-F1 (%) ↑ |
|------|--------|--------|--------------|
| De-En| Transformer                  | 34.4\(^†\) | -            |
|      | DynamicConv                  | 35.2\(^†\) | -            |
|      | DynamicConv + MoEx           | 35.46±0.06 | 67.28±0.02   |
|      |                               | 35.64±0.11 | 67.44±0.09   |
| En-De| DynamicConv                  | 28.96±0.05 | 63.75±0.04   |
|      | DynamicConv + MoEx           | 29.18±0.10 | 63.86±0.02   |
| It-En| DynamicConv                  | 33.27±0.04 | 65.51±0.02   |
|      | DynamicConv + MoEx           | 33.36±0.11 | 65.65±0.07   |
| En-It| DynamicConv                  | 30.47±0.06 | 64.05±0.01   |
|      | DynamicConv + MoEx           | 30.64±0.06 | 64.21±0.11   |

Table 6. Classification errors (%) on ModelNet10 and ModelNet40. The mean and standard error out of 3 runs are reported.

**Results.** Table 7: Machine translation with DynamicConv (Wu et al., 2019a) on IWSLT-14 German to English, English to German, Italian to English, and English to Italian tasks. The mean and standard error are based on 3 random runs. \(^†\): numbers from Wu et al. (2019a).

Note: for all these scores, the higher the better.

| Task   | Method | BLEU ↑ | BERT-F1 (%) ↑ |
|--------|--------|--------|--------------|
| De-En  | Transformer | 34.4\(^†\) | -    |
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|        | DynamicConv + MoEx | 29.18±0.10 | 63.86±0.02 |
| It-En  | DynamicConv  | 33.27±0.04 | 65.51±0.02 |
|        | DynamicConv + MoEx | 33.36±0.11 | 65.65±0.07 |
| En-It  | DynamicConv  | 30.47±0.06 | 64.05±0.01 |
|        | DynamicConv + MoEx | 30.64±0.06 | 64.21±0.11 |

Table 7. Machine translation with DynamicConv (Wu et al., 2019a) on IWSLT-14 German to English, English to German, Italian to English, and English to Italian tasks. The mean and standard error are based on 3 random runs. \(^†\): numbers from Wu et al. (2019a). Note: for all these scores, the higher the better.

### 4.5. Machine Translation on IWSLT 2014

**Setup.** To show the potential of MoEx on natural language processing tasks, we apply MoEx to the state-of-the-art DynamicConv (Wu et al., 2019a) model on 4 tasks in IWSLT 2014 (Cettolo et al., 2014): German to English, English to German, Italian to English, and English to Italian machine translation. IWSLT 2014 is based on the transcripts of TED talks and their translation, it contains 167K English and German sentence pairs and 175K English and Italian sentence pairs. We use fairseq library (Ott et al., 2019) and follow the common setup (Edunov et al., 2018b) using 1/23 of the full training set as the validation set for hyper-parameter selection and early stopping. All models are trained with a batch size of 12000 tokens per GPU on 4 GPUs for 20K updates to ensure convergence; however, the models usually don’t improve after 10K updates. We use the validation set to select the best model. We tune the hyper-parameters of MoEx on the validation set of the German to English task including \(p \in \{0.25, 0.5, 0.75, 1\}\) and \(\lambda \in \{0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}\) and use MoEx with InstanceNorm with \(p = 0.5\) and \(\lambda = 0.8\) after the first encoder layer. We apply the same set of hyper-parameters to
the other three language pairs. When computing the moments, the edge paddings are ignored. We use two metrics to evaluate the models: BLEU (Papineni et al., 2002) which is an exact word-matching metric and BERTScore 8 (Zhang et al., 2020). We report the scaled BERT-F1\textsuperscript{9} for better interpretability. As suggested by the authors, we use multilingual BERT (Devlin et al., 2019) to compute BERTScore for non-English languages\textsuperscript{10} and RoBERTa-large for English\textsuperscript{11}. Result. Table 7 summarizes the average scores (higher better) with standard error rates over three runs. It shows that MoEx consistently improves the baseline model on all four tasks by about 0.2 BLEU and 0.2% BERT-F1. Although these improvements are not exorbitant, they are highly consistent and, as far as we know, MoEx is the first label-perturbing data augmentation method that improves machine translation models.

5. Ablation Study and Model Analysis

5.1. Ablation Study on Components

| name                        | MoEx | Test Error |
|-----------------------------|------|------------|
| Baseline                    | ✗    | 26.3±0.10  |
| Label smoothing (Szegedy et al., 2016) | ✗    | 26.0±0.06  |
| Label Interpolation only    | ✗    | 26.0±0.12  |
| MoEx (λ = 1, not interpolating the labels) | ✔    | 26.3±0.02  |
| MoEx with label smoothing   | ✔    | 25.8±0.09  |
| MoEx (λ = 0.9, label interpolation, proposed) | ✔    | 25.5±0.09  |

Table 8. Ablation study on different design choices.

In the previous section we have established that MoEx yields significant improvements across many tasks and model architectures. In this section we shed light onto which design choices crucially contribute to these improvements. Table 8 shows results on CIFAR-100 with a Resnet-110 architecture, averaged over 3 runs. The column titled MoEx indicates whether we performed moment exchange or not.

Label smoothing. First, we investigate if the positive effect of MoEx can be attributed to label smoothing (Szegedy et al., 2016). In label smoothing, one changes the loss of a sample x with label y to

$$\lambda \ell(x, y) + \frac{1}{C-1} \sum_{y' \neq y} (1 - \lambda) \ell(x, y'),$$  

where C denotes the total number of classes. Essentially the neural network is not trained to predict one class with 100% certainty, but instead only up to a confidence of λ.

Further, we evaluate Label Interpolation only. Here, we evaluate MoEx with label interpolation - but without any feature augmentation, essentially investigating the effect of label interpolation alone. Both variations yield some improvements over the baseline, but are clearly significantly worse than MoEx.

Interpolated targets. The last three rows of Table 8 demonstrate the necessity of utilizing the moments for prediction. We investigate two variants: λ = 1, which corresponds to no label interpolation; MoEx with label smoothing (essentially assigning a small loss to all labels except \(y_A\)). The last row corresponds to our proposed method, MoEx (\(\lambda = 0.9\)). Two general observations can be made: 1. interpolating the labels is crucial for MoEx to be beneficial — the approach leads to absolutely no improvement when we set \(\lambda = 1\). 2. it is also important to perform moment exchange, without it MoEx reduces to a version of label smoothing, which yields significantly smaller benefits.

| Moments to exchange | Test Error |
|---------------------|------------|
| No MoEx             | 26.3±0.10  |
| All features in a layer, i.e. LN | 25.6±0.02 |
| Feature in each channel, i.e. IN | 25.7±0.13 |
| Features in Group of channels, i.e. GN (g=4) | 25.7±0.09 |
| Features at each position, i.e. PONO | **25.5±0.09** |
| 1st moment at each position | 25.9±0.06 |
| 2nd moment at each position | 26.0±0.13 |
| Unnormalized 2nd moment at each position, i.e. LRN | 26.3±0.05 |

Table 9. MoEx with different normalization methods on CIFAR-100. For each normalization, we report the mean and standard error of 3 runs with the best configuration.

Choices of normalizations. We study how MoEx performs when using moments from LayerNorm (LN) (Ba et al., 2016), InstanceNorm (IN) (Ulyanov et al., 2016), PONO (Li et al., 2019), GroupNorm (GN) (Wu & He, 2018), and local response normalization (LRN) (Krizhevsky et al., 2012) perform. For LRN, we use a recent variant (Karras et al., 2018) which uses the unnormalized 2nd moment at each position. We conduct experiments on CIFAR-100 with ResNet110. For each normalization, we do a hyper-parameter sweep to find the best setup\textsuperscript{12}. Table 9 shows classification results of MoEx with various feature normalization methods.

\textsuperscript{8}BERTScore is a newly proposed evaluation metric for text generation based on matching contextual embeddings extracted from BERT or RoBERTa (Devlin et al., 2019; Liu et al., 2019) and has been shown to be more correlated with human judgments.

\textsuperscript{9}https://github.com/Tiiger/bert-score/blob/master/journal/rescale_base.md

\textsuperscript{10}Hash code: bert-base-multilingual-cased_1.0_no-idf, version=0.3.0 (hug\textsubscript{trans}=2.3.0)-rescaled

\textsuperscript{11}Hash code: roberta-large_1.17_no-idf_version=0.3.0 (hug\textsubscript{trans}=2.3.0)-rescaled

\textsuperscript{12}We select the best result from experiments with \(\lambda \in \)
on CIFAR-100 averaged over 3 runs (with corresponding standard errors). We observe that MoEx generally works with all normalization approaches, however PONO has a slight but significant edge, which we attribute to the fact that it catches the structural information of the feature most effectively. Different normalizations work the best at different layers. With PONO we apply MoEx in the first layer, whereas the LN moments work best when exchanged after the second stage of a 3-stage ResNet-110; GN and IN are better at the first stage. We hypothesize the reason is that PONO moments captures local information while LN and IN compute global features which are better encoded at later stages of a ResNet. For image classification, using PONO seems generally best. For some other tasks we observe that using moments from IN can be more favorable (See Subsec. 4.4 and 4.5).

5.2. Ablation Study on Hyper-parameters

$\lambda$ and $1-\lambda$ serve as the target interpolation weights of labels $y_A$, $y_B$, respectively. To explore the relationship between $\lambda$ and model performance, we train a ResNet50 on ImageNet with $\lambda \in \{0.3, 0.5, 0.7, 0.9\}$ with on PONO. The results are summarized in Table 10. We observe that generally higher $\lambda$ leads to lower error, probably because more information is captured in the normalized features than in the moments. After all, moments only capture general statistics, whereas the features have many channels and can capture texture information in great detail. We also investigate various values of the exchange probability $p$ (for fixed $\lambda = 0.9$), but on the ImageNet data $p = 1$ (i.e. apply MoEx on every image) tends to perform best.

5.3. Robustness and Uncertainty.

To estimate the robustness of the models trained with MoEx, we follow the procedure proposed by Hendrycks et al. (2019) and evaluate our models on their ImageNet-A data set, which contains 7500 natural images (not originally part of ImageNet) that are misclassified by a publicly released ResNet-50 in torchvision\textsuperscript{13}. We compare our models with various publicly released pretrained models including Cutout (Zhang et al., 2018), Mixup (Zhang et al., 2018), CutMix (Yun et al., 2019), Shape-Resnet (Geirhos et al., 2018), and recently proposed AugMix (Hendrycks et al., 2020). We report all 5 metrics implemented in the official evaluation code\textsuperscript{14}; model accuracy (Acc), root mean square calibration error (RMS), mean absolute distance calibration error (MAD), the area under the response rate accuracy curve (AURRA) and soft F1 (Sokolova et al., 2006; Hendrycks et al., 2019). Table 11 summarizes all results. In general MoEx performs fairly well across the board. The combination of MoEx and Cutmix leads to the best performance on most of the metrics.

6. Conclusion and Future Work

In this paper we propose MoEx, a novel data augmentation algorithm. Instead of disregarding the moments extracted by the (intra-instance) normalization layer, it forces the neural network to pay special attention towards them. We show empirically that this approach is consistently able to improve the classification accuracy and robustness. As an augmentation method for features, MoEx is complementary to existing state-of-the-art approaches and can be readily combined with them. Beyond vision tasks, we also apply MoEx on speech and natural language processing tasks. As future work we plan to investigate alternatives to feature normalization for the invertible functions $F$. For instance, one could factorize the hidden features, or learn decompositions (Chen et al., 2011). Further, $F$ can also be learned using models like invertible ResNet (Behrmann et al., 2019) or flow-based methods (Tabak et al., 2010; Rezende & Mohamed, 2015).

\textsuperscript{13}https://download.pytorch.org/models/resnet50-19c8e357.pth
\textsuperscript{14}https://github.com/hendrycks/natural-adv-examples
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Appendices

A. Additional Experiments

A.1. Fintuneing Imagenet pretrained models on Pascal VOC for Object Detection

Setup. To demonstrate that MoEx encourages models to learn better image representations, we apply models pretrained on ImageNet with MoEx to downstream tasks including object detection on Pascal VOC 2007 dataset. We use the Faster R-CNN (Ren et al., 2015) with C4 or FPN (Lin et al., 2017) backbones implemented in Detectron2 (Wu et al., 2019b) and following their default training configurations. We consider three ImageNet pretrained models: the ResNet-50 provided by He et al. (2015), our ResNet-50 baseline trained for 300 epochs, our ResNet-50 trained with CutMix (Yun et al., 2019), and our ResNet-50 trained with MoEx. A Faster R-CNN is initialized with these pretrained weights and finetuned on Pascal VOC 2007 + 2012 training data, tested on Pascal VOC 2007 test set, and evaluated with the PASCAL VOC style metric: average precision at IoU 50% which we call AP\textsubscript{VOC} (or AP50 in detectron2). We also report MS COCO (Lin et al., 2014) style average precision metric AP\textsubscript{COCO} which is recently considered as a better choice. Notably, MoEx is not applied during finetuning.

Results. Table 12 shows the average precision of different initializations. We discover that MoEx provides a better initialization than the baseline ResNet-50 and is competitive against CutMix (Yun et al., 2019) for the downstream cases and leads slightly better performance regardless of backbone architectures.

| Backbone | Initialization | AP\textsubscript{VOC} | AP\textsubscript{COCO} |
|----------|----------------|-------------------|-------------------|
| C4       | ResNet-50 (default) | 80.3 | 51.8 |
|          | ResNet-50 (300 epochs) | 81.2 | 53.5 |
|          | ResNet-50 + CutMix | 82.1 | 54.3 |
|          | ResNet-50 + MoEx | 81.6 | 54.6 |
| FPN      | ResNet-50 (default) | 81.8 | 53.8 |
|          | ResNet-50 (300 epochs) | 82.0 | 54.2 |
|          | ResNet-50 + CutMix | 82.1 | 54.3 |
|          | ResNet-50 + MoEx | 82.3 | 54.3 |

Table 12. Object detection on PASCAL VOC 2007 test set using Faster R-CNN whose backbone is initialized with different pretrained weights. We use either the original C4 or feature pyramid network (Lin et al., 2017) backbone.

B. MoEx Pytorch Implementation

Algorithm 1 shows an example code of MoEx in PyTorch.

```python
def moex(x, y, norm_type):
    x, mean, std = normalization(x, norm_type)
    ex_index = torch.randperm(x.shape[0])
    x = x * std[ex_index] + mean[ex_index]
    y_b = y[ex_index]
    return x, y, y_b
```

```python
def interpolate_loss(output, y, y_b, loss_func, lam):
    return lam * loss_func(output, y) + \
    (1. - lam) * loss_func(output, y_b)
```

```python
def normalization(x, norm_type, epsilon=1e-5):
    # decide how to compute the moments
    if norm_type == 'pono':
        norm_dims = [1]
    elif norm_type == 'instance_norm':
        norm_dims = [2, 3]
    else: # layer norm
        norm_dims = [1, 2, 3]
    # compute the moments
    mean = x.mean(dim=norm_dims, keepdim=True)
    var = x.var(dim=norm_dims, keepdim=True)
    std = (var + epsilon).sqrt()
    # normalize the features, i.e., remove the moments
    x = (x - mean) / std
    return x, mean, std
```

Algorithm 1. Example code of MoEx in PyTorch.