Distortion Robust Image Classification using Deep Convolutional Neural Network with Discrete Cosine Transform

Md Tahmid Hossain  Shyh Wei Teng  Dengsheng Zhang  Suryani Lim  Guojun Lu
School of Science, Engineering and Information Technology
Federation University, Gippsland Campus, Churchill, VIC 3842, Australia
{mt.hossain,shyh.wei.teng,dengsheng.zhang,suryani.lim,guojun.lu}@federation.edu.au

Abstract

Convolutional Neural Network is good at image classification. However, it is found to be vulnerable to image quality degradation. Even a small amount of distortion such as noise or blur can severely hamper the performance of these CNN architectures. Most of the work in the literature strives to mitigate this problem simply by fine-tuning a pre-trained CNN on mutually exclusive or a union set of distorted training data. This iterative fine-tuning process with all known types of distortion is exhaustive and the network struggles to handle unseen distortions. In this work, we propose distortion robust DCT-Net, a Discrete Cosine Transform based module integrated into a deep network which is built on top of VGG16 [1]. Unlike other works in the literature, DCT-Net is “blind” to the distortion type and level in an image both during training and testing. As a part of the training process, the proposed DCT module discards input information which mostly represents the contribution of high frequencies. The DCT-Net is trained (“blindly”) only once and applied in generic situation without further retraining. We also extend the idea of traditional dropout and present a training adaptive version of the same. We evaluate our proposed method against Gaussian blur, motion blur, salt and pepper noise, Gaussian noise and speckle noise added to CIFAR-10/100 [2] and ImageNet [3] test sets. Experimental results demonstrate that once trained, DCT-Net not only generalizes well to a variety of unseen image distortions but also outperforms other methods in the literature.

1. Introduction

Back-propagation and gradient based learning [4,5] ushered a new era in the field of machine learning and artificial intelligence. The ImageNet challenge [6] has induced a number of new image classification architectures starting from AlexNet [7] to even deeper networks like ZFNet [8], VGGNet [1], ResNet [9], GoogleNet [10]. However, these deep networks are found to be susceptible to image distortion as far as classification is concerned [11–16]. It is observed that adding a little amount of distortion in the test set leads the network to misclassify an object as something else with surprisingly high confidence: some as high as
provides further visual evidence
concludes this paper.

This paper is organized as follows: Section 2 sheds light on our motivation behind this work. Section 3 discusses related works. In Section 4, we introduce and formulate the proposed DCT-Net with adaptive dropout. In Section 5, we discuss about the data sets and provide a performance comparison of existing works with our proposed approach. Section 6 concludes this paper.

2. Motivation

Most of the well established deep networks (AlexNet [7], ResNet [9], GoogleNet [10], VGG16 [1]) presume that the input images are of artifact-free, high quality and both the training and test datasets of these networks reflect this assumption. However, in real-life scenarios, images can get distorted during acquisition, transmission or even by delib-
erration. For example, while capturing, image sensor can exhibit noise in low light conditions. Motion/Gaussian blur can occur if the camera or subject is moving/shaking or due to focusing error. In transmission, packet-loss can poten-
tially result in missing regions of the image, noise, or missing frequencies, depending on how the image is encoded. Moreover, there are situations where surveillance images are taken in challenging conditions (low light, rain, snow, fast moving object etc.) or the device used is of substandard quality resulting in degraded visual data. Addition-
ally, with the advent of a wide range of cellular phones and hand-held devices, the requirement of high-quality im-
agery to perform different computer vision related tasks may need to be relaxed. Distortion or substandard image quality can also degrade the performance of a CNN based system in other computer vision tasks as well e.g. object
detection, image retrieval, image registration, segmentation and even more complex tasks like autonomous car driving,
facial recognition-based security systems etc.

All these facts inspired us to explore ways of overcoming the drawbacks of traditional CNN. Our proposed DCT-Net’s aim is to solve this issue by learning a more robust representation of the training data. Since noise and blur cause the greatest degradation in a convolutional neural network’s performance [12, 14, 19], we focus on these two types of distortion in this work. We have found that training the deep network with DCT module enables our deep network to perform well on unseen distortions and thereby achieves substantial invariance against quality degradation.

The DCT module transforms each input image to frequency domain via Discrete Cosine Transform [20, 21]. In order to discard input information and image details during training, DCT module eliminates certain DCT coefficients based on one randomly chosen threshold per image. The random threshold value $X$ is selected for each new training input from a standard uniform distribution of integers where, $X \sim U[0, 50]$. When $X$ happens to be 0, the image does not get transformed at all and is fed forward in the input’s original form. Values close to 50, on the other hand, removes more detail from the image. It is worth noting that most of the discarded DCT coefficients belong to high frequency and therefore discarding them contributes to loss of image details as depicted in Figure 2. Since the DCT based loss of input information or image detail is random for each image, every epoch of our deep network’s training process yields a different representation of each original training data. The input diversity induced by the DCT module ameliorates the learning process and enables the network to excel when tested on unseen distortions. The process is explained elaborately in Section 4.

3. Related Work

Despite the deep network’s vulnerability to small image perturbations [13, 15] or quality degradation [11], not a lot has been done to solve this problem. A simple approach to add robustness to neural networks is to fine-tune the network on images with the expected distortions. Vasiljevic et al. [22] show that this approach works well for blurred images. They achieve satisfactory performance on clean and blurred test sets and their training data consists of half clean and half blurred images. Similarly, Zhou et al. [23] show the effectiveness of fine-tuning for both noisy and blurry images. Interestingly, the model trained on both noisy and blurry images has a much higher error rate than the average error rate of models trained only on noise and blur when these latter models are tested on their respective distorted or degraded test sets. Our results section shed further light on this aspect. Dodge et al. [12] propose a mixture of experts-based model for image classification (MixQualNet) that is more robust to distorted data than single fine-tuned models. Their proposed network architecture consists of expert networks where the experts are trained for particular distortion types and a gating network which is trained to select among the experts. This model shows better performance compared to [22, 23]. However, MixQualNet is effectively a complex ensemble of $N$ number of identical CNN models where $N$ is the number of distortion types the model is trained on. This already parameter heavy model has 1 million additional gating network parameters all resulting in a sluggish training process. Diamond et al. [24] and Yim et al. [14] propose a system that modifies a neural network with additional layer or channels that serve to undistort the images by denoising and deblurring. For these reconstructed images, further fine-tuning of a deep neural network is performed. The method has prior knowledge of camera noise and blurring parameters, but for general applications (e.g. images from the internet) the camera parameters may be unavailable. This drawback greatly limits the feasibility of the method.

To reduce data overfitting during training, constant dropout probability [17, 25] is used in the literature. The dropout probability ($P$) used in VGG16 [1] is fixed at 0.5. Evaluation results in Section 5 will show that the proposed training adaptive incremental dropout enables the deep network to generalize better.

4. DCT-Net

In this section, we introduce our proposed DCT-Net which takes the form of a VGG16 [1] architecture with the integration of the DCT module and training adaptive dropout. We make use of Discrete Cosine Transform to select and eliminate a set of frequency coefficients from each of the training images. Section 5 which assesses the results, quantitatively demonstrates that once trained, the proposed DCT-Net not only achieves considerable robustness against a variety of quality degraded test sets but also maintains consistent performance on clean or original data.

4.1. Discrete Cosine Transform

Discrete Cosine Transform is a widely used technique to analyze signals in the frequency domain. It has found its way into numerous applications, from lossy compression of audio (e.g. MP3) and image (e.g. JPEG) to spectral methods for the numerical solution of partial differential equations. To perform The Forward DCT (FDCT) in a standard JPEG compression [26], each image is divided into $8 \times 8$ blocks; effectively a 64-point discrete signal. However, it is found that this block-wise DCT operation may lead to undesired properties like blocking artifacts [27, 28]. Therefore, we consider only one block with dimensions equivalent to the height ($H$) and width ($W$) of the original input image. FDCT takes $H \times W$ signal as its input and outputs the corresponding basis-signal amplitudes or DCT coefficients. The DCT coefficient values can thereby be regarded as the rel-
ative amount of the 2D spatial frequencies contained in the original input signal, which in our case is an image. One of the most important features of FDCT is that it concentrates most of the signal energy in a few transformed DCT coefficients in the lower spatial frequencies [26, 29]. In other words, the number of DCT coefficients with substantially high magnitude is very low and the smaller coefficients are far greater in number. More often than not, bulk of the information in a natural image is represented in lower frequencies. Higher frequencies generally encode sharp changes that add extremely fine detail to the image.

There are a number of ways to perform DCT in the literature [30]. However, we make use of Fast Cosine Transform (FCT) [20, 21] because of its computational efficiency ($N\log N$). We make use of Equation 1 on an input image $A$ for FDCT and Equation 2 for Inverse DCT (IDCT) to obtain the reconstructed image $B$.

$$B_{pq} = \alpha_p\alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \left( \frac{2(m+1)p}{2M} \right) \cos \left( \frac{2(n+1)q}{2N} \right),$$

$$0 \leq p \leq M - 1, 0 \leq q \leq N - 1$$

(1)

Where,

$$\alpha_p = \begin{cases} \sqrt{\frac{2}{M}}, & p = 0. \\ \sqrt{\frac{2}{M}}, & 1 \leq p \leq M - 1 \end{cases}$$

$$\alpha_q = \begin{cases} \sqrt{\frac{2}{N}}, & q = 0. \\ \sqrt{\frac{2}{N}}, & 1 \leq q \leq N - 1 \end{cases}$$

And the Inverse DCT (IDCT) is performed by:

$$A_{mn} = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} \alpha_p\alpha_q B_{pq} \cos \left( \frac{2(m+1)p}{2M} \right) \cos \left( \frac{2(n+1)q}{2N} \right),$$

$$0 \leq m \leq M - 1, 0 \leq n \leq N - 1$$

(2)

Where,

$$\alpha_p = \begin{cases} \sqrt{\frac{2}{M}}, & p = 0. \\ \sqrt{\frac{2}{M}}, & 1 \leq p \leq M - 1 \end{cases}$$

$$\alpha_q = \begin{cases} \sqrt{\frac{2}{N}}, & q = 0. \\ \sqrt{\frac{2}{N}}, & 1 \leq q \leq N - 1 \end{cases}$$

Here $M$ and $N$ are the row and column size of the input and output images respectively.

### 4.2. DCT Module Integration

The DCT module in the DCT-Net (Figure 3) transforms each of the training images using FDCT and produces a set of DCT coefficients. A uniform random variable $X$ is chosen for each training image from a predefined range of $0$ to $50$ ($X \sim U[0, 50]$) which is effectively a random DCT coefficient threshold value. All the DCT coefficients lying under the chosen threshold $X$ are turned zero. From a superficial point of understanding, when the random threshold is equal to or close to 0, the input image undergoes very little or no transformation at all which means there is hardly any loss of input information or image detail. On the other hand, if the random threshold happens to be a large number which is close to 50, this thresholding step removes most of the high frequencies from an image and leaves most of the lower frequencies intact along with the DC component. Since a large part of the signal strength is stored in the lower spectrum, the loss of information takes away mostly sharp changes and finer details of the image pertaining to different edges and contours. Along with the omission of most of the high frequencies, some of the lower frequencies with little visual impact on the input image may get discarded as well in the process. It is worth noting that the thresholding considers the absolute values of the coefficients. Inverse DCT or IDCT is performed on the remaining DCT coefficients to reconstruct the transformed image. This DCT transformed image is then fed forward to the first convolutional layer. The modus operandi of the proposed DCT module is presented in Algorithm 1.

The DCT module is free of trainable parameters and no backpropagation based learning takes place within this module. Once the deep network is trained, this module is removed from the network and test images directly enter into the first convolutional layer. Figure 2 depicts a sample image pair of DCT transformed training data from ImageNet. It can be visually observed that higher the threshold value, greater the loss of information or image detail.

### 4.3. Deep Network

VGG16 is found to be the most resilient deep network against image degradation [12, 32]. Therefore, we employ this particular CNN model as the base of our proposed DCT-
ReLUs are used as activation functions followed by each convolutional layer and the fully connected layer except the last one. Adaptive dropout is used only in the fully connected layer. The proposed DCT module followed by the input layer is responsible for transforming the input according to Algorithm 1. By discarding information, this module generates a wide range of representations of each image during training.

Networks are tested against these five types of quality degradation. Original VGG16 uses $3 \times 3$ filters in all thirteen convolutional layers, ReLU is used as activation function, $2 \times 2$ max pooling with stride 2 and 1000 channel softmax and classification output layer. All the weights are initialized on ImageNet for our network training.

Dropout is a well-known technique to counter the effect of data overfitting [17]. We extend the idea of dropout and deploy an adaptive version of it during training. The dropout probability $P$ is initialized with 0.1 at the beginning of training and updated from a range of [0.1 - 0.5] with the smallest increment unit of 0.1. The update only comes into effect when the network seems to converge to training data and the possibility of overfitting is inevitable. $P$ is updated when minibatch training accuracy reaches and stays above...
5. Results

In this section, we present and discuss the performance of different deep networks on a number of benchmark data sets. In addition to the original test set, we evaluate the networks on five different types of distortion namely Gaussian noise, Gaussian blur, salt and pepper noise, motion blur and speckle noise.

5.1. Datasets

We consider CIFAR-10, CIFAR-100 [2] and ImageNet [3] as our benchmark datasets. CIFAR-10 consists of 60,000 $32 \times 32 \times 3$ images in 10 classes, with 6,000 images per class. The split is 50,000 training images and 10,000 test images. CIFAR-100 has 100 classes containing 600 images each. There are 500 training images and 100 testing images per class. Dimensions of these images are same as CIFAR-10. In ImageNet, there are 1000 object classes and approximately 1.2 million training images, 50,000 validation images and 100,000 test images.

5.2. Test Data

Gaussian noise is added to an image with the variance ranging from 0.1 to 0.5. For the Gaussian blur kernel, the standard deviation used is between 0 to 5 for CIFAR-10/100 and 0 to 10 for ImageNet. Salt and pepper noise is replicated by turning on and off pixels with a predefined probability. We add salt and pepper noise to an image pixel with a probability varying from 0 to 0.5. For motion blur kernel in CIFAR-10/100, we use motion angle range between 0 to 22.5 degree because of the small spatial dimension of the dataset. The number of pixels is set to 10 as linear motion parameter. As the spatial dimension is greater in ImageNet, we use a motion angle range of 0 to 45 degree with the number of pixels set to 15 as linear motion parameter. We add multiplicative speckle noise to an image $I$ and produce 80% for an entire epoch. The value of $P$ depends on the remaining number of epochs which is divided into five equal intervals. As the training proceeds forward, $P$ increases in each of the five epoch intervals by 0.1.

Because of the smaller image dimensions in CIFAR-10/100, we modified the original VGG16 input layer from $224 \times 224 \times 3$ to $32 \times 32 \times 3$ and to maintain regularity of the network, the dimensions of the first and second fully connected layers are reduced to 512 from 4096. The original 1000 way softmax and classification output layers are replaced with 10 and 100 for CIFAR-10 and CIFAR-100 respectively. We use stochastic gradient descent (SGD) with momentum value 0.9, data shuffling before every epoch while training. We have used 40 epochs with minibatch size set to 128. Initial learning rate was set to 0.01. We make use of proposed adaptive dropout and L2 regularization to counter overfitting [33, 34].
## 5.3. Performance Comparison

We refer our model as DCT-Net in this work which is based on the VGG16 architecture with adaptive dropout. We denote $\mathbf{M}_{\text{clean}}$ as the VGG16 network trained on the original clean dataset. $\mathbf{M}_{\text{Gnoise}}$ and $\mathbf{M}_{\text{Gblur}}$ [22] are effectively $\mathbf{M}_{\text{clean}}$ fine-tuned on Gaussian noise and blur containing training set respectively. $\mathbf{M}_{\text{BN}}$ [23] is the model which is fine-tuned on both Gaussian blur and noise. $\mathbf{M}_{\text{All}}$ is the VGG16 network fine-tuned on all five distortions mentioned in this work. Finally, MixQualNet is the ensemble of individual distortion expert models with a gating network [12].

Table 1 compares the classification accuracy of these base models. All of the deep networks are tested against five increasing levels of corresponding type of noise and blur. The levels are uniformly chosen between the minimum and maximum distortion range specified in Section 5.2. The mean accuracy over all distortion levels is displayed in Table 1 except the overall accuracy.

Table 1. Performance comparison of different network architectures on the clean and distorted test sets of CIFAR-10/100 and ImageNet. Accuracy over each type of distorted test sets is the mean over the distortion levels specified in Section 5.2. Overall accuracy is the network’s average accuracy across clean and distorted datasets. The best accuracy is displayed in bold and the second best is underlined.

### CIFAR-10

| CNN Model       | Original | Gaussian Noise | Salt and Pepper Noise | Speckle Noise | Gaussian Blur | Motion Blur | Overall Accuracy |
|-----------------|----------|----------------|-----------------------|--------------|---------------|-------------|------------------|
| $\mathbf{M}_{\text{clean}}$ (VGG16 [1]) | 88.43    | 40.53          | 42.60                 | 45.10        | 61.43         | 56.35       | 55.74            |
| $\mathbf{M}_{\text{Gnoise}}$ | 65.50    | 62.91          | 59.10                 | 54.32        | 23.50         | 20.36       | 47.60            |
| $\mathbf{M}_{\text{Gblur}}$ [22]  | 68.84    | 29.33          | 30.25                 | 38.36        | 73.36         | 50.51       | 48.44            |
| $\mathbf{M}_{\text{BN}}$ [23]   | 83.36    | 59.06          | 51.87                 | 55.08        | 69.36         | 52.98       | 61.95            |
| $\mathbf{M}_{\text{All}}$     | 80.54    | 57.95          | 60.77                 | 63.12        | 68.14         | 59.20       | 64.95            |
| MixQualNet [12]   | 81.56    | 60.69          | 58.99                 | 57.36        | 70.26         | 62.89       | 65.29            |
| DCT-Net$_{\text{NoAdaptiveDropout}}$ | 85.36    | 55.87          | 59.02                 | 61.39        | 76.41         | 68.51       | 67.76            |
| DCT-Net             | 86.97    | 57.06          | 61.23                 | 62.05        | 77.15         | 70.91       | 69.23            |

### CIFAR-100

| CNN Model       | Original | Gaussian Noise | Salt and Pepper Noise | Speckle Noise | Gaussian Blur | Motion Blur | Overall Accuracy |
|-----------------|----------|----------------|-----------------------|--------------|---------------|-------------|------------------|
| $\mathbf{M}_{\text{clean}}$ (VGG16 [1]) | 67.49    | 25.52          | 29.62                 | 32.91        | 50.39         | 48.30       | 42.37            |
| $\mathbf{M}_{\text{Gnoise}}$ | 52.54    | 49.80          | 59.22                 | 41.20        | 17.61         | 14.25       | 39.10            |
| $\mathbf{M}_{\text{Gblur}}$ [22]  | 56.81    | 19.69          | 22.26                 | 27.35        | 62.37         | 42.77       | 38.54            |
| $\mathbf{M}_{\text{BN}}$ [23]   | 62.44    | 46.08          | 38.28                 | 33.03        | 52.46         | 35.88       | 44.70            |
| $\mathbf{M}_{\text{All}}$     | 60.68    | 45.13          | 60.20                 | 61.39        | 53.32         | 49.10       | 54.97            |
| MixQualNet [12]   | 63.50    | 45.89          | 58.01                 | 57.61        | 55.22         | 49.83       | 55.01            |
| DCT-Net$_{\text{NoAdaptiveDropout}}$ | 64.30    | 44.11          | 60.25                 | 60.39        | 62.32         | 53.50       | 57.48            |
| DCT-Net             | 65.39    | 44.85          | 62.33                 | 60.65        | 64.05         | 55.91       | 58.86            |

### ImageNet

| CNN Model       | Original | Gaussian Noise | Salt and Pepper Noise | Speckle Noise | Gaussian Blur | Motion Blur | Overall Accuracy |
|-----------------|----------|----------------|-----------------------|--------------|---------------|-------------|------------------|
| $\mathbf{M}_{\text{clean}}$ (VGG16 [1]) | 92.60    | 32.45          | 15.32                 | 24.98        | 29.53         | 25.67       | 36.76            |
| $\mathbf{M}_{\text{Gnoise}}$ | 49.60    | 55.31          | 40.21                 | 33.55        | 11.95         | 10.66       | 33.55            |
| $\mathbf{M}_{\text{Gblur}}$ [22]  | 55.36    | 16.24          | 18.91                 | 22.63        | 39.88         | 30.69       | 30.62            |
| $\mathbf{M}_{\text{BN}}$ [23]   | 75.77    | 54.25          | 42.30                 | 38.65        | 30.14         | 27.85       | 44.83            |
| $\mathbf{M}_{\text{All}}$     | 74.12    | 49.22          | 45.35                 | 44.22        | 38.32         | 40.50       | 48.79            |
| MixQualNet [12]   | 72.85    | 50.68          | 49.63                 | 47.34        | 39.33         | 34.98       | 49.14            |
| DCT-Net$_{\text{NoAdaptiveDropout}}$ | 85.35    | 52.12          | 50.66                 | 50.30        | 42.25         | 39.77       | 53.41            |
| DCT-Net             | 87.50    | 52.98          | 51.30                 | 50.98        | 43.90         | 41.32       | 54.66            |

A noisy image $J$, where $J = I + n \ast I$, $n$ is a uniformly distributed random noise. Variance ranging from 0.1 to 0.5 is used for speckle noise. All the test images are tested at five different distortion levels uniformly chosen from the defined range of distortions. A set of sample test image pairs with increasing level of distortion can be seen in Figure 4.
first and last one. For a particular network, the original accuracy in Table 1 is computed over the corresponding clean test set whereas the overall accuracy in the last column is the numerical average over all six individual accuracies. It is worth noticing that the models fine-tuned on one specific type of distortion e.g. $M_{\text{Gnoise}}$ and $M_{\text{Gblur}}$ [22] perform well on their specific distorted test set. However, they fail to generalize well to other types of distortion and also accuracy on the clean test data drops.

On the other hand, $M_{\text{BN}}$ [23] has a mediocre performance on all the test sets and could not surpass $M_{\text{Gnoise}}$ and $M_{\text{Gblur}}$ in their particular distortion test sets in any of the benchmark data set. Moreover, the performance of $M_{\text{BN}}$ propels the belief that the poor performance of these networks on unseen distortion remains a major drawback.

$M_{\text{All}}$ and MixQualNet [12] displays competitive results in a number of test sets but the rigid training image requirement with all possible distortions should be kept in mind. The accuracy displayed by $M_{\text{All}}$ and MixQualNet [12] seem to be similar across all three datasets. The overall accuracy of $M_{\text{All}}$ and MixQualNet is 64.95%, 54.97%, 48.79% and 65.29%, 55.01%, 49.14% in CIFAR-10, CIFAR-100 and ImageNet respectively. This is consistent with the ways these networks are designed and trained. MixQualNet is basically an ensemble of expert networks trained on specific distortions augmented by a weight sharing gating network. $M_{\text{All}}$, on the other hand, is fine-tuned on those specific distortions with a single network.

Our proposed DCT-Net is found to ameliorate the standards and copes well with all types of image distortion, outperforming contemporary models on overall accuracy in all three datasets (69.23% in CIFAR-10, 58.86% in CIFAR-100 and 54.66% in ImageNet). It also demonstrates consistent accuracy on each type of distortion that is introduced while negligible drop in performance on the original clean test set.

Figure 5 further sheds light on the performance of DCT-Net with and without adaptive dropout and MixQualNet [12] on ImageNet over the specified levels of distortions. It is visually evident that with increasing magnitude of distortion in the test sets, all three networks struggle to maintain classification accuracy. DCT-Net displays better consistency under increasing level of distortion which is consistent with the results in Table 1.

6. Conclusion

We have proposed DCT-Net with an adaptive dropout and show that discarding part of the input signal or image detail based on Discrete Cosine Transform adds diversity to each of the training data. Since the threshold used for discarding information is random for each image, every epoch is likely to produce a different version of a training image. This way, the network gets to learn a strong feature representation from all the variants of an image. Our deep network does not heavily rely anymore on fine details for an object to be recognized and therefore becomes able to correctly classify degraded (noisy or blurry) images. Contrary to traditional fine-tuning process on specific distortions, the introduced DCT-Net is "blindly" trained only once and shows impressive accuracy on unseen distortions on a number of benchmark data sets.

Although image classification has been the center of attention in this work, Substandard image quality can adversely affect the performance of any other computer vision task that relies on neural networks e.g. object detection [35–37], image segmentation [38] etc. Our proposed method can easily be applied in other existing networks which further adds to the contribution of this work.

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