Knowledge Distillation Thrives on Data Augmentation

Huan Wang2* Suhas Lohit1† Michael Jones1 Yun Fu2

1Mitsubishi Electric Research Laboratories, Cambridge, MA, USA
2Northeastern University, Boston, MA, USA

Abstract

Knowledge distillation (KD) is a general deep neural network training framework that uses a teacher model to guide a student model. Many works have explored the rationale for its success, however, its interplay with data augmentation (DA) has not been well recognized so far. In this paper, we are motivated by an interesting observation in classification: KD loss can benefit from extended training iterations while the cross-entropy loss does not. We show this disparity arises because of data augmentation: KD loss can tap into the extra information from different input views brought by DA. By this explanation, we propose to enhance KD via a stronger data augmentation scheme (e.g., mixup, CutMix). Furthermore, an even stronger new DA approach is developed specifically for KD based on the idea of active learning. The findings and merits of the proposed method are validated by extensive experiments on CIFAR-100, Tiny ImageNet, and ImageNet datasets. We can achieve improved performance simply by using the original KD loss combined with stronger augmentation schemes, compared to existing state-of-the-art methods, which employ more advanced distillation losses. In addition, when our approaches are combined with more advanced distillation losses, we can advance the state-of-the-art performance even more. On top of the encouraging performance, this paper also sheds some light on explaining the success of knowledge distillation. The discovered interplay between KD and DA may inspire more advanced KD algorithms.

1. Introduction

Deep neural networks are the best performing machine learning method in many fields of interest [13, 25]. How to effectively train a deep network in classification has been a central topic for decades. In the past several years, efforts have mainly focused on (1) better architecture design (e.g., batch normalization [9], residual blocks [4], dense connections [8]) and (2) better loss functions (e.g., label smoothing [29, 17], contrastive loss [7], large-margin softmax [14]) than the standard cross-entropy (CE) loss. Knowledge distillation (KD) [6] is a general training framework that falls in the second group. In the KD framework, a stronger network (called teacher) is introduced to guide the learning of the original network (called student) by minimizing the discrepancy between the representations of the two networks.

\[ \mathcal{L}_{KD} = (1 - \alpha)\mathcal{L}_{CE}(y, p(s)) + \alpha \tau^2 \mathcal{D}_{KL}(p(t)/\tau, p(s)/\tau), \]

where \( \mathcal{D}_{KL} \) represents KL divergence [12]; \( \alpha \in (0, 1) \) is a factor to balance the two loss terms; \( \mathcal{L}_{CE} \) denotes the cross-entropy loss; \( y \) is the one-hot label and \( p(t), p(s) \) stands for the teacher’s output and student’s output, respectively; \( \tau \) is a temperature constant [6] to smooth predicted probabilities. KD allows us to train smaller, more efficient neural

* Work done when Huan Wang was an intern at MERL.
† Corresponding author is Suhas Lohit: slohit@merl.com.
networks without compromising on accuracy, which facilitates deploying deep learning onto mobile devices and in other resource constrained environments. The effectiveness of KD has been seen in many tasks [2, 33, 10, 34]. Meanwhile, many works have been investigating the reason behind its success, such as class similarity structure [6] and regularization [36]. However, few works have paid attention to its interplay with the input data augmentation (DA), a kind of techniques to obtain more data through various transformations [27]. In this paper, we will show that data augmentation is also an important explaining factor in the success of KD. Moreover, based on our findings we can achieve much better performance simply by using the original KD loss when combined with a strong DA scheme.

Our proposed algorithms are inspired from an interesting observation shown in Figure 1, where we plot the student test error rate when it is trained for different numbers of epochs using the cross-entropy loss and knowledge distillation loss, with or without data augmentation, respectively. As seen, when data augmentation is employed (the two figures in the right column), KD loss can bring down the test error when trained for more epochs. In contrast, the CE loss does not benefit from this more training iterations (even worse, when trained for too long, like 960 epochs – 4 times the usual training time – the error rate actually goes up because of overfitting). Meanwhile, if the data augmentation is removed (the two figures in the left column), the advantage of KD loss over CE loss with more training iterations disappears – both the two losses degrade the performance if trained for much more epochs. These tell us that, KD and DA, as two common techniques to improve the performance of a deep neural network, are actually not independent. There is an interplay between them, which we will show can be leveraged to obtain stronger performance.

Specifically, we propose a framework in this paper to explain the observation aforementioned. Because of the random transformations in data augmentation, the input data is not fixed over different epochs. One input actually presents multi-views of it. When the KD loss is used, the teacher maps these multi-views to different targets for the student to learn. As illustrated in Figure 2(a), these targets with different probability structures can reveal more information in the data, thus helping the student even more. In contrast, when CE loss is adopted, the target is fixed regardless of the different views of the input, and the extra information is lost. The introduced concept of input views not only explains the observation above, but also leads us to a plausible new direction to improve KD, that is, by creating more diverse input views. Therefore, we propose to employ stronger data augmentation techniques to enhance the KD performance (without changing the loss objectives), building upon two advanced data augmentation schemes, mixup [40] and CutMix [37]. Finally, we further exploit the idea of active learning [26] to develop an even stronger new data augmentation method specifically for knowledge distillation.

In short, our contributions in this work can be summarized into four main points as follows:

- We uncover an interesting phenomenon of the interplay between knowledge distillation and data augmentation and propose a framework to explain it.

- Building upon our explanation, we propose to enhance the original KD loss with stronger data augmentation schemes (mixup [40] and CutMix [37]). It will be shown that these methods can see a more reasonable application in the KD case than in the CE case.

- We further propose an even stronger data augmentation method specifically for knowledge distillation, referring to the idea of active learning [26].

- Empirically, we achieve better results simply by using the original KD loss combined with the proposed DA scheme, compared to state-of-the-art KD methods, which adopt more advanced distillation losses.

2. Related Work

Knowledge distillation. The general idea of knowledge distillation is to guide the training of a student model through a stronger pretrained teacher model (or an ensemble of learning models). It was pioneered by Bucilă et al. [1] and later refined by Hinton et al. [6], who coined the term. Since its debut, knowledge distillation has seen extensive application in vision and language tasks [2, 33, 10, 34]. Many variants have been proposed regarding the central question in knowledge distillation, that is, how to define the knowledge that is supposed to be transferred from the teacher to the student. Examples of such knowledge definitions include feature distance [23], feature map attention [39], feature distribution [20], activation boundary [5], inter-sample distance relationship [19, 22, 15, 31], and mutual information [30]. Over the past several years, the progress has been made primarily from the output end (i.e., through a better loss function). In contrast to previous works, our goal in this paper is to improve the KD performance from the input end with the help of data augmentation. We will show this path is as effective and also has much potential for future work.

Data augmentation. Deep neural networks are prone to overfitting, i.e., building input-target connection using undesirable or irrelevant features (like noise) in the data. Data augmentation is a prevailing technique to curb overfitting [27]. In classification tasks, data augmentation aims to explicitly provide data with label-invariant transformations (such as random crop, horizontal flip, color jittering)
Figure 2. Interplay between knowledge distillation (KD) and data augmentation (DA). (a) Illustration of the difference of supervised target between the KD loss and cross-entropy (CE) loss. An input is transformed to different versions (called views in our paper) owing to data augmentation. KD loss can provide extra information to the student by mapping these views to different targets, while the CE loss cannot. (b) Illustration of knowledge distillation with the proposed data augmentation framework. The standard DA consists of random crop and horizontal flip. The stronger DA refers to any data augmentation scheme more advanced than the standard one. In this paper, we have explored three stronger DA: mixup [40], CutMix [37], and our proposed CutMix-pick (Section 3.2) (this figure is best viewed in color).

in the training so that the model can learn representations robust to those nuisance factors. Recently, some advanced data augmentation methods were proposed, which not only transform the input, but also transform the target based on certain corresponding relations. For example, mixup [40] linearly mixes two images with the labels mixed by the same linear interpolation; manifold mixup [32] is similar to mixup but conducts the mix operation in the feature level instead of pixel level; CutMix [37] pastes a patch cut from an image onto another image with the label decided by the area ratio of the two parts. Now that the input and target are transformed simultaneously, the key is to maintain a semantic correspondence between the new input and new target. Although these methods have been proven effective, one lingering concern is about the reasoning behind them. Specifically, it is easy to come up with examples where the semantic correspondence is poorly kept (see Figure 5 for examples on CutMix). Unlike these methods, which focus on general classification using the cross-entropy loss, our work investigates the interplay between data augmentation and knowledge distillation loss and the proposed new data augmentation is specifically for knowledge distillation.

3. Proposed Method

3.1. Interplay of KD, DA, and training iterations

We first introduce a framework to explain the interesting phenomena that (1) KD loss can benefit from more training iterations while CE loss cannot when data augmentation is present; (2) when DA is absent, the advantage of KD over CE disappears. Training for more iterations means presenting more examples to the network. Over iterative training, the presented examples are not exactly the same among different epochs because of the random transformations of data augmentation. Different versions of an images produced by data augmentation can be regarded as multi-views of that image [35, 30]. We term this kind of data difference as input view diversity. As depicted in Figure 2(a), when the CE loss is employed, different views of an image are mapped to a single point in the target space (their hard label). In contrast, when the KD loss is used, different views of the data are mapped to a group of points in the target space through the teacher, which can reveal richer information around that class. By richer, we specifically mean two sources: First is the class structure information provided by using soft labels instead of the hard labels, namely, the “dark knowledge” [6]. Second is the information provided by the different input views from data augmentation. For a concrete example, in Figure 2(a), although the three views of the input share the same main class “dog”, the target probability structures are different: compared with the first view, the second one has more lawn in it, thus the teacher has larger predicted probability in the “lawn” class; similarly, the third view has more sunshine, thus larger probability in the “sunset” class. These subtle information structures are beneficial for the student to learn. However, if the CE loss is used, all the three views are mapped to the same one-hot label, not putting the extra information to good use. Using more training iterations keeps producing new data views, which can expose more of the teacher’s knowledge. Thus, it can constantly boost the student performance. For the CE loss, as the target is fixed for different views, no new information is provided as supervision. Hence, the CE loss cannot benefit from longer training. When data augmentation is removed, there are no new data views at all, therefore, the KD loss cannot boost the student performance any more.
The proposed framework not only explains the interesting finding in Section 1, but also points us in a new direction to improve KD: by providing more diverse data views via stronger data augmentation so that more of the teacher’s knowledge can be exposed to the student.

3.2. Proposed algorithms for improved KD

(1) mixup/CutMix + KD. We continue our exploration with two existing data augmentation techniques that are more advanced than the standard random crop and flip: mixup [40] and CutMix [37]. Specifically, let \( x_0 \) denote the raw data, \( x \) denote the transformed data by the standard augmentation (random crop and flip). Illustrated in Figure 2(b), we propose to add mixup/CutMix following \( x \) to obtain \( x' \). Unlike the common data augmentation where only the transformed input is fed into the network, we keep both the input \( x \) and \( x' \) for the training (thus, the number of input examples during training is increased). The consideration of keeping both inputs is to maintain the information path for the original input \( x \) so that we can easily see how the added information path of \( x' \) leads to a difference.

For the \( x \) part, its loss is still the original KD loss made up of both the cross-entropy loss and the KL divergence (Equation 1); for the \( x' \) part, its loss is only the KL divergence. We do not use the labels assigned by mixup or CutMix because they can be misleading as we will show later (Figure 5). Notably, not using the hard label actually has an additional implication. A dataset augmentation scheme which employs CE loss has to supply corresponding labels as supervisory information. Thus, in order to maintain the semantic correspondence, it cannot permit very “extreme” transformations for data augmentation. In contrast, in the mixup/CutMix+KD setting described above, the data augmentation scheme need not worry about the labels as they are assigned by the teacher model. Therefore, a larger set of transformations can be allowed to improve the data view diversity, which we will show is beneficial to KD.

Between mixup [40] and CutMix [37], we will show CutMix is more favorable in our experiments (Table 1) (and both of them are significantly better than the standard augmentation, random crop and flip). Therefore, we choose CutMix [37] as the base augmentation scheme to develop our next algorithm as follows.

(2) CutMix-Pick + KD. Our next algorithm is an even stronger DA scheme tailored to KD, based on the idea of active learning [26]. In active learning, the learner enjoys the freedom to query the data instances to be labelled for training by an oracle (i.e., the teacher in our case) [26]. Since the augmented data can vary in their quality, we can introduce certain criterion to pick the more valuable data for the student. Clearly, the key is how to define the criterion. We tap into the idea of hard examples [18] to realize this. Specifically, we measure the hardness by the KL divergence between the teacher’s output and the student’s output,

\[
d = D_{KL}(p^{(t)}/\tau, p^{(s)}/\tau).
\]

We sort the augmented samples by their \( r \)’s in ascending order and pick a subset with the largest \( d \)’s. Notably, the criterion \( d \) has exactly the same form that the student is supposed to minimize in Equation (1); while here we pick samples to maximize it. This design makes an adaptive competition: when the student is updated, the criterion made of the KL divergence will also be updated. Each time, it makes sure the hardest samples are selected for the student.

Other common choices for the criterion include the teacher’s entropy or the student’s entropy (larger entropy implying more uncertainty means the sample is harder). They only take into account one-side information, either the teacher’s or student’s, so conceivably they are not as good as the KL divergence criterion, which considers the information from both sides. This choice will be empirically justified in our experiments (Table 2).

4. Experimental Results

Datasets and networks. We evaluate our method on the CIFAR-100 [11], Tiny ImageNet\(^1\), and ImageNet [3] object recognition datasets. CIFAR-100 has 100 object classes (32×32 RGB images). Each class has 500 images for training and 100 images for testing. ImageNet is now the most standard large-scale benchmark dataset in image classification, which has 1000 classes (224×224 RGB images), over 1.2 million images in total. Tiny ImageNet is a small version of ImageNet with 200 classes (64×64 RGB images). Each class has 500 images for training, 50 for validation and 50 for testing. To thoroughly evaluate our methods, we benchmark them on various standard network architectures: VGG [28], ResNet [4], WRN (Wide-ResNet) [38], MobileNetV2 [24], ShuffleNetV2 [16]. Our code and trained models will be made publicly available.

Evaluated methods. In addition to the standard cross-entropy training and the original KD method [6], we also compare with the state-of-the-art distillation approach CRD [30]. It is important to note that our method focuses on improving KD from the input end, while CRD improves KD from the output end (i.e., a better loss function). Therefore, they are orthogonal and we will show they can be combined together to deliver even better results.

Hyperparameter settings. The temperature \( \tau \) of knowledge distillation is set to 4. Loss weight \( \alpha = 0.9 \) (Equation (1)). (1) For CIFAR-100 and Tiny ImageNet, training batch size is 64; the original number of total training epochs is 240, with learning rate decayed at epoch 150, 180, and

\(^1\)https://tiny-imagenet.herokuapp.com/
Figure 3. Test error rate of WRN-16-2 and VGG8 on CIFAR-100 when trained for different numbers of epochs, using KD or cross-entropy (CE) loss, with or without data augmentation (DA). The original number of training iterations is 240 epochs. Every error rate is averaged by 3 random runs (shaded area represents the standard deviation). Consistent with Figure 1, KD benefits from more training iterations while CE does not when DA is employed; when DA is removed, both KD and CE do not benefit from more training iterations.

| Number of total training epochs | Without DA, KD | With DA, KD | Without DA, CE | With DA, CE |
|--------------------------------|---------------|------------|---------------|------------|
| 240                            | 37.5          | 38.0       | 38.5          | 39.0       |
| 360                            | 39.5          | 40.0       | 41.0          | 42.0       |

Table 1. KD test accuracy comparison when using different DA schemes. The standard one consists of random crop and flip.

210 by multiplier 1/10. The initial lr is 0.05. (2) For ImageNet, training batch size is 256; the original number of training epochs is 100, with learning rate decayed at epoch 30, 60, 90. The initial learning rate is 0.1. All these settings are the same with CRD [30] for fair comparison with it. Note, in our experiments we will show the results of more training iterations. If the number of total epochs is scaled by a factor k, the epoch of decaying learning rate will also be scaled proportionally. For example, if we train a network for 480 epochs in total, the epochs after which the learning rate is decayed will be 300, 360, and 420.

We use PyTorch [21] to conduct all our experiments. For CIFAR-100, we adopt the pretrained teacher models from CRD2 for fair comparison with it. For Tiny ImageNet, we train our own teacher models. For ImageNet, we adopt the standard torchvision models3.

**4.1. CIFAR-100**

Effect of more training iterations. In Section 1, we presented Figure 1 to show that KD loss can benefit from more training iterations while the cross-entropy loss cannot. Here we show more results in Figure 3 on different network architectures to confirm the finding is more general. In line with the ResNet case (Figure 1), longer-training also brings clear performance gains with KD loss on WRN and VGG. The gains are more or less up to the particular pairs but the trends are consistent: (1) Using data augmentation, KD can benefit from more training iterations while CE cannot; (2) Not using data augmentation, both KD and CE can hardly benefit from more training iterations.

**Exploring different data augmentation schemes.** In Table 1 we compare three different data augmentation schemes on the CIFAR-100 dataset – the standard (random crop and flip referring to common PyTorch implementation), mixup [40] and CutMix [37]. It has been shown in the papers of mixup and CutMix that they improve accuracy over the standard data augmentation. By our analysis, stronger data augmentation should boost KD more, which is verified in the table. CutMix is best in two out of the
three pairs, better than mixup, thus we choose it as our base scheme to develop a more advanced augmentation method.

**Exploring different data picking schemes.** In Table 2, we compare the three potential schemes of selecting more informative data for the student: entropy of the teacher’s output (“T ent.”), entropy of the student output (“S ent.”), and the KL divergence between the teacher’s and student’s outputs (“T/S kld”). As shown, the KL divergence scheme performs best. This is expected as either the teacher entropy or student entropy alone does not reveal the whole picture. Large KL divergence serves our purpose better.

**Benchmark on CIFAR-100.** The results on CIFAR-100 are presented in Table 3. We have the following observations. (1) KD can be consistently improved simply by training for more iterations (960 epochs vs. the original 240 epochs), as we analyze in Section 3.2, owing to the effect of data augmentation. (2) Comparing the row of “KD+CutMix” with the row of “KD”, we see the proposed scheme of adopting CutMix for augmentation improves the accuracies of all teacher-student pairs. And on 5 out of the 7 pairs, the improvement is more than 1 percentage point. (3) Comparing the row of “KD+CutMix-pick” to that of “KD+CutMix”, we see 6 out of the 7 pairs are improved further, showing the proposed data picking scheme works better in most cases. (4) Finally, “KD+CutMix-pick” scheme can be combined with more training iterations, which delivers even higher accuracies. (5) If comparing our best results (“KD+CutMix-pick_{960}”) with those of CRD (though this is not an apples-to-apples comparison since the two methods focus on different aspects to improve KD), we can see our approach outperforms CRD on 6 out of the 7 pairs. It is worth emphasizing that we achieve this simply using the original KD loss [6], with no special loss design. This justifies one of our motivations in this paper, i.e., existing KD methods [22, 19, 30] mainly improve KD from the output through better loss functions, while we propose to improve KD from the input and show this path is just as promising.

In the last two rows of Figure 3, when CRD [30], the state-of-the-art KD algorithm, is armed with our proposed “CutMix-pick” and more training iterations, its results can be further advanced consistently. This demonstrates that the proposed schemes are general and can work seamlessly with those methods focusing on better KD loss functions.

**Further remarks.** Regarding the observation (1) stated above, it actually has another implication to the community than just as a method to improve the performance of KD. It tells us that the number of training iterations can have a big impact on the performance of a KD method. Unaware of this issue, if authors of a paper on knowledge distillation compare their method to others by directly citing numbers from other papers and the training epochs happen to be different, then the comparison may well be unintentionally unfair from the beginning. In this sense, our finding can greatly help the community to standardize the benchmarks of different KD methods, paying particular attention to the total training iterations and data augmentation schemes.

### 4.2. Tiny ImageNet

In this section we evaluate the proposed schemes on a more challenging dataset – Tiny ImageNet. Similar to the case on CIFAR-100, we have results on different teacher-student pairs, shown in Table 4. For more training iterations, we train for 480 epochs instead of 960 to save time. Most claims on the CIFAR-100 dataset are also validated here: (1) “KD+CutMix” is better than KD, which is verified on all pairs. (2) “KD+CutMix-pick” is better than “KD+CutMix”, verified on 6 pairs. The exception pair is ResNet56/ResNet20, where adding data picking decreases the accuracy slightly by 0.11%. (3) When “KD+CutMix-pick” is equipped with more training iterations, we obtain the best performance. The main difference lies in the comparison between “KD_{480}” and “KD”. In the CIFAR-100
case with standard augmentation, more training iterations consistently improves the accuracy on all 7 pairs, while here only 3 are improved. We conceive this may be attributed to the dataset itself. The simple random crop and flip augmentation scheme cannot produce such diverse data views on this more challenging dataset. Using our CutMix-pick augmentation scheme, more training iterations does show improvement in 7 out of 7 cases.

Similar to the case on CIFAR-100, here we also evaluate the compatibility of our approaches with the state-of-the-art CRD method, shown in the last two rows of Figure 4. Our method “CutMix-pick” can further advance the prior state-of-the-art on 5 pairs. Exceptions are WRN-40-2/WRN-16-2 and ResNet56/ResNet20. When CRD+CutMix-pick is trained for more epochs (480 instead of 240), further improvement can be seen on 6 of 7 pairs.

### 4.3. ImageNet

We further evaluate our methods on the ImageNet dataset, as shown in Table 5. “KD+CutMix200” manages to boost the student top-1/top-5 accuracy by 0.56%/0.55%. When the proposed data picking scheme is added, it does not see similar improvement as for CIFAR-100 and Tiny ImageNet, but does not hurt the performance either (the accuracies are still clearly better than the original KD).

**Under-performance case analysis.** Here we investigate why the proposed data picking scheme under-performs on ImageNet in contrast to its promising performance on CIFAR-100 and Tiny ImageNet. The picking scheme is proposed based on the idea of active learning (see Section 3.2). Intuitively, it can work only if the picked data has more information to the student network than those randomly presented. Since we adopt the KL divergence between the teacher’s output and the student’s output to measure the amount of information in the input data, we can compare this metric on two different sets of data, i.e., picked randomly vs. picked based on KL divergence. Specifically, we define average KL divergence ratio

\[ r = \frac{1}{N} \sum_{i=1}^{N} \frac{d_i}{\sum_{j=1}^{N} d_j}, \]

where \( d_i \) stands for the KL divergence for the \( i \)-th sample defined in Equation (2); \( N \) denotes the number of total samples in a batch; \( N_p \) denotes the number of sample picked based on KL divergence (\( N_p = N/2 \) in our experiments); note that \( r > 1 \). Larger \( r \) means the picked samples have more information than the average samples. Then we compare \( r \) on different datasets over the training process of “KD+CutMix-pick”. Results are shown in Figure 4. As seen, in terms of \( r \), CIFAR-100 > Tiny ImageNet > ImageNet on average; meanwhile, comparing the results of CIFAR-100 (Table 3), Tiny ImageNet (Table 4), and ImageNet (Table 5) we will see the accuracy gains brought by data picking also pose the same trend of CIFAR-100 > Tiny ImageNet > ImageNet, in accordance with our expectation. This validates the soundness of the metric \( r \) we introduced. The \( r \) on ImageNet is clearly lower than the other two, meaning there is no significant information difference between the picked data and the average data, which may well explain the under-performance of the data picking scheme on ImageNet. Note that the root cause of this problem actually lies in the data augmentation part – since it cannot produce more informative samples, the subsequent data picking has no scope to show its value. How to obtain an even stronger scheme than CutMix remains elusive for now, which we will investigate as part of our future work.

**CutMix sample analysis.** During the KD training of ResNet34/ResNet18 on ImageNet, we recorded the CutMix samples on which the teacher disagrees with the CutMix scheme on the label. We call this label disagreement issue. As show in Figure 5, there exist cases where the image cut
among them, many suffer from the problem shown in Figure 4: the teacher predicted the input end instead of a better loss function, which may not make sense anymore. Similar problem appears on (b). Note that these misleading labels by CutMix are rectified when the teacher is employed to guide the student. The teacher assigns the correct label “cab” to (a) and “Yorkshire terrier” to (b) (which is still not the true label “Tibetan terrier” but it is clearly more relevant and “Tibetan terrier” is also in the top-5 predictions). For (c) and (d), they pose a problem more than occlusion: the foreground cut in (c) is labelled as “acoustic guitar”, however, the cut is too small for us to make it out without knowing the label. Meanwhile, the background object “Arabian camel” happens to be occluded. Then the grids in the picture turn out to be the most salient part. If we look at the predictions of the teacher, “shopping cart” and “shopping basket” clearly make more sense than either of the original two labels. Similar issue happens on (d), where the “Indian elephant” is largely occluded, the foreground cut labelled as “quill” but the bottle in the middle is more salient. Thus the teacher predicted it as “coffeepot”, “milk can”, etc. In order to see how severe the label disagreement issue is, we counted the number of these synthetic samples and found that on more than half of the samples (52.1%) produced by CutMix, the teacher model and CutMix hold a different view regarding the label. Among them, many suffer from the problem shown in Figure 5 and the KD loss can rectify these label mistakes. This further shows the interplay between KD and DA: KD thrives on DA and in turn, some DA schemes also make more sense in the KD setting than in the cross-entropy setting.

5. Conclusion

Many papers have been exploring the reason behind the success of knowledge distillation. However, its interplay with data augmentation is missed from prior exploration. In this paper, we bridge the gap by systematically investigating how knowledge distillation thrives on data augmentation. The findings inspire us to enhance knowledge distillation using stronger data augmentation building upon existing data techniques (e.g., mixup and CutMix). An even stronger data augmentation scheme is further proposed specifically for knowledge distillation, using ideas from active learning. Extensive experiments demonstrate the merits of our methods across various networks on CIFAR-100, Tiny ImageNet, and ImageNet, with comparison to the state-of-the-art. On top of the encouraging performances, for the first time our work shows the potential of boosting KD from the input end instead of a better loss function, which may inspire more stronger KD methods to come forward if a stronger data augmentation scheme is found. Our paper can also help the community to build a more standard benchmark of knowledge distillation algorithms, paying attention to weight-carrying factors like number of training iterations.

Table 5. Top-1 and Top-5 accuracy (%) of the student ResNet18 on ImageNet validation set. Pretrained ResNet34 (from torchvision models) is adopted as the teacher. The best results are in bold and second best underlined. The subscript 200 indicates the total number of training epochs is 200 (the original one is 100).

| Teacher  | Student  | KD [6] | KD+CutMix200 (ours) | KD+CutMix-pick200 (ours) | SP [31] | AT [39] | CRD [30] |
|----------|----------|--------|---------------------|--------------------------|---------|---------|---------|
| Top-1 Accuracy | 73.31 | 69.75 | 70.66 | 71.22 | 71.20 | 70.62 | 70.70 | **71.38** |
| Top-5 Accuracy | 91.42 | 89.07 | 89.88 | 90.43 | 90.45 | 89.80 | 90.00 | **90.49** |

Figure 4. Mean KL divergence ratio $r$ (Equation 3) over iterations on different datasets. CIFAR: CIFAR-100, Tiny: Tiny ImageNet, Res: ResNet, WRN: WideResNet. The iterations are normalized into range $[0, 1]$ for easy comparison since the total numbers of iterations are different on the three datasets (best viewed in color).

Figure 5. ImageNet CutMix samples where the main object in one of the images is no longer visible after CutMix augmentation. Below each sample, the first is the target probability assigned by CutMix and the second is the top-5 predicted probabilities by the teacher. These examples can be misleading when cross-entropy loss is used, but not for KD, as explained in the text.
References

[1] Cristian Buciluă, Rich Caruana, and Alexandru Niculescu-Mizil. Model compression. In SIGKDD, 2006. 2
[2] Guobin Chen, Wongun Choi, Xiang Yu, Tony Han, and Manmohan Chandraker. Learning efficient object detection models with knowledge distillation. In NeurIPS, 2017. 2
[3] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In CVPR, 2009. 4
[4] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, 2016. 1, 4
[5] Byeongho Heo, Minsik Lee, Sangdoo Yun, and Jin Young Choi. Knowledge transfer via distillation of activation boundaries formed by hidden neurons. In AAAI, 2019. 2
[6] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. In NeurIPS Workshop, 2014. 1, 2, 3, 4, 6, 7, 8
[7] Geoffrey E Hinton. Training products of experts by minimizing contrastive divergence. Neural Computation, 14(8):1771–1800, 2002. 1
[8] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In CVPR, 2017. 1
[9] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In ICML, 2015. 1
[10] Xiaoliang Liu, Yinhua Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. Tinybert: Distilling bert for natural language understanding. arXiv preprint arXiv:1909.10351, 2019. 2
[11] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009. 4
[12] Solomon Kullback. Information theory and statistics. Courier Corporation, 1997. 1
[13] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436, 2015. 1
[14] Wei Li and Zhiheng Yu, Meng Yang. Large-margin softmax loss for convolutional neural networks. In ICML, 2016. 1
[15] Yufan Liu, Jiajiong Cao, Bing Li, Chunfeng Yuan, Weiming Zhang, Yu Liu, Shunfeng Zhou, and Zhaoning Zhang. Correlation congruence for knowledge distillation. In ICCV, 2019. 2, 6
[16] Ningning Ma, Xin Jiang, Wei Dong, Richard Socher, Li-Jia Li, and Kai Li. Knowledge distillation via distillation of activation boundaries formed by hidden neurons. In AAAI, 2019. 2
[17] Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? In NeurIPS, 2019. 1
[18] Gaurav Kumar Nayak, Konda Reddy Mopuri, Vaisakh Shah, Venkatesh Babu Radhakrishnan, and Anirban Chakraborty. Zero-shot knowledge distillation in deep networks. In ICML, 2019. 4
[19] Wonyoo Park, Dongju Kim, Yan Lu, and Minsu Cho. Relational knowledge distillation. In CVPR, 2019. 2, 6
[20] Nikolaos Passalis and Anastasios Tefas. Learning deep representations with probabilistic knowledge transfer. In ECCV, 2018. 2
[21] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. In NeurIPS, 2019. 5
[22] Baoyun Peng, Xiao Jin, Jiaheng Liu, Dongsheng Li, Yichao Wu, Yu Liu, Shunfeng Zhou, and Zhaoning Zhang. Correlation congruence for knowledge distillation. In ICCV, 2019. 2, 6
[23] Adrian Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. Fitnets: Hints for thin deep nets. In ICLR, 2015. 2
[24] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In CVPR, 2018. 4
[25] Jürgen Schmidhuber. Deep learning in neural networks: An overview. Neural Networks, 61:85–117, 2015. 1
[26] Pillars Settles. From theories to queries: Active learning in practice. In AISTATS Workshop on Active Learning and Experimental Design, 2011. 2, 4
[27] Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. Journal of Big Data, 6(1):60, 2019. 2
[28] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, 2015. 4
[29] Yosman Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In CVPR, 2016. 1
[30] Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive representation distillation. In ICLR, 2020. 2, 3, 4, 5, 6, 7, 8
[31] Frederick Tung and Greg Mori. Similarity-preserving knowledge distillation. In CVPR, 2019. 2, 8
[32] Vikas Verma, Alex Lamb, Christopher Beckham, Amir Najafi, Ioannis Mitliagkas, David Lopez-Paz, and Yoshua Bengio. Manifold mixup: Better representations by interpolating hidden states. In ICML, 2019. 3
[33] Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, and Minghsuan Yang. Collaborative distillation for ultra-resolution universal style transfer. In CVPR, 2020. 2
[34] Lin Wang and Kuk-Jin Yoon. Knowledge distillation and student-teacher learning for visual intelligence: A review and new outlooks. arXiv preprint arXiv:2004.05937, 2020. 2
[35] Zhirong Wu, Yu Liu, Shunfeng Zhou, and Zhaoning Zhang. Knowledge distillation via distillation of activation boundaries formed by hidden neurons. In ICML, 2019. 2
[36] Zhizhong Wu, Yuanjun Xiong, Stella X Yu, and Dahua Lin. Unsupervised feature learning via non-parametric instance discrimination. In CVPR, 2018. 3
[37] Lijun Yuan, Francis EH Tay, Guilin Li, Tao Wang, and Jiashi Feng. Revisiting knowledge distillation via label smoothing regularization. In CVPR, 2020. 2
[38] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In ICCV, 2019. 2, 3, 4, 5
[39] Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. In BMVC, 2016. 4
[39] Sergey Zagoruyko and Nikos Komodakis. Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer. In *ICLR*, 2017.

[40] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In *ICLR*, 2018.