Self-distillation with Batch Knowledge Ensembling Improves ImageNet Classification

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Abstract

The recent studies of knowledge distillation [26, 37, 43, 13] have discovered that ensembling the "dark knowledge" from multiple teachers or students contributes to creating better soft targets for training, but at the cost of significantly more computations and/or parameters. In this work, we present BAtch Knowledge Ensembling (BAKE) to produce refined soft targets for anchor images by propagating and ensembling the knowledge of the other samples in the same mini-batch. Specifically, for each sample of interest, the propagation of knowledge is weighted in accordance with the inter-sample affinities, which are estimated on-the-fly with the current network. The propagated knowledge can then be ensembled to form a better soft target for distillation. In this way, our BAKE framework achieves online knowledge ensembling across multiple samples with only a single network. It requires minimal computational and memory overhead compared to existing knowledge ensembling methods. Extensive experiments demonstrate that the lightweight yet effective BAKE consistently boosts the classification performance of various architectures on multiple datasets, e.g., a significant +1.2% gain of ResNet-50 on ImageNet with only +3.7% computational overhead and zero additional parameters. BAKE does not only improve the vanilla baselines, but also surpasses the single-network state-of-the-arts [5, 52, 49, 54, 48] on all the benchmarks.

1. Introduction

Deep neural networks have achieved impressive success on computer vision tasks, where image classification [16, 47, 35, 41, 53] is considered as one of the most fundamental tasks given the wide range of applications of its learned representations and their transferability to down-

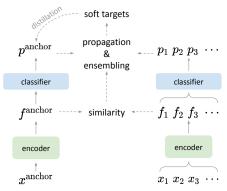


Figure 1. BAtch Knowledge Ensembling (BAKE) produces soft targets for self-distillation with a single network (an encoder and a classifier). For an anchor image $x^{\rm anchor}$, the knowledge of the other samples $\{x_1, x_2, x_3, \cdots\}$ in the same batch is weightedly propagated and ensembled to form a better soft targets for distillation on-the-fly. Note that $x^{\rm anchor}$ and $\{x_1, x_2, x_3, \dots\}$ are fed into the same network. This method enables knowledge ensembling with minimal computational and memory overhead.

stream tasks, *e.g.*, detection [34, 27], segmentation [56, 15], generation [57, 22, 29, 10], retrieval [7, 6, 8, 9], *etc.* There is a tremendous number of methods [1, 2, 46, 13, 52, 49, 51] working on improving the image classification accuracy, especially on the large-scale ImageNet [4] dataset.

Recent studies [1, 2, 51] have shed light on the limitations of supervised learning of image classification. They have observed that the imperfect learning targets resulted from manually annotated ground-truth labels (one-hot class vectors) turn out to be a key factor that hinders the further improvement of classification accuracy. Thanks to the great success of knowledge distillation [20], the soft probability vectors predicted by a teacher network, carrying the learned "dark knowledge", can serve as informative training super-

visions to enhance a student network. The quality of the teacher's predictions is found critical to the accuracy of the student network. State-of-the-art methods [26, 37, 43, 13] have found that multiple teachers or students could encode complementary knowledge and their "ensembled" soft targets are more robust learning objectives. Positive as their results are, they depend on extra networks or branches, undoubtedly increasing the computational and memory cost to a noticeable extent.

To produce high-quality soft targets with minimal cost, we introduce a self-distillation method with a novel **BAtch K**nowledge **E**nsembling (**BAKE**) scheme, as illustrated in Figure 1. Rather than ensembling multiple networks or branches to generate the distillation soft targets, our method only adopts a single network. It achieves knowledge ensembling by on-the-fly aggregating the "dark knowledge" from different samples within the same mini-batch, yielding better soft targets.

Specifically, given the samples' encoded representations and predictions in a mini-batch, we conduct cross-sample knowledge ensembling under the assumption that visually similar samples with close-by representations should encode consistent class-wise predictions. In practice, for each anchor sample, the other samples' predictions ("dark knowledge") can be weightedly propagated and ensembled to form a soft target. The knowledge propagation and ensembling are conducted iteratively until convergence, i.e., the soft targets no longer change. In order to perform the proposed batch knowledge ensembling at each training iteration efficiently, we adopt approximate inference to estimate the iterative knowledge ensembling results. After properly ensembling the samples' knowledge in the batch, we are able to create refined soft targets for each sample to improve the training of image classification.

We demonstrate the effectiveness of our proposed BAKE via a comprehensive set of evaluations with various architectures and datasets. On ImageNet [4] classification, BAKE well boosts the top-1 accuracy of ResNet-50 [16] by a significant +1.2% gain $(76.8\% \rightarrow 78.0\%)$ with a negligible 3.7% computational overhead at training. The network trained by BAKE shows consistent improvements for transfer learning on downstream tasks, including detection [34] and segmentation [15] on COCO [28]. BAKE also improves the classification robustness on perturbed datasets [11, 18, 19] at test time. Not only improving the accuracy on ImageNet, BAKE also improves the classification accuracies on CIFAR-100 [24], TinyImageNet, CUB-200-2011 [45], MIT67 [32] and Stanford Dogs [23]. BAKE substantially outperforms the single-network state-of-thearts [5, 52, 49, 54, 48] on all the benchmarks.

The contributions of our method are three-fold. (1) We for the first time introduce to produce ensembled soft targets for self-distillation without using multiple networks

	No extra parameters	Ensembled knowledge
Self-distillation [5, 54, 48, 52]	V	×
Ensemble distillation [26, 37, 43, 13]	×	~
Label refinery [1, 2, 51]	×	×
Our BAKE	✓	✓

Table 1. Key differences between our method and related works.

or additional network branches. (2) We propose a novel batch knowledge ensembling mechanism to online refine the distillation targets with the cross-sample knowledge, *i.e.*, weightedly aggregating the knowledge from other samples in the same batch. (3) Our method is simple yet consistently effective on improving classification performances of various networks and datasets with minimal computational overhead and zero additional parameters.

2. Related Works

Knowledge distillation. Knowledge distillation [20] aims to transfer the "dark" knowledge learned from a highcapacity teacher network to a student network via soft labels. The soft labels can be the class probabilities [5, 13, 52] or the feature representations [44, 31] output by the teacher, containing more complete structured information than the one-hot ground-truth labels. The distillation process can be formed by a "teacher-student" framework [20, 37], a "peerteaching" framework [26, 55, 13], or a self-distillation framework [5, 54, 48, 52]. Our BAKE is mostly related to the self-distillation methods, i.e., teaching a single network using its own knowledge. However, most of them [5, 54] only considered the knowledge of individual instances, resulting in sub-optimal learning targets. Recent works introduced to preserve the predictive consistency between intraimage (original v.s. perturbed) [48] or intra-class (images out of the same class) [52] samples. However, they only focused on pairwise images, carrying limited information compared to the ensembled batch knowledge of BAKE. More importantly, they simply defined the positive pairs using constant instance or class IDs, which may incur false supervisions as their visual features might be actually dissimilar, especially after the random crop augmentation [39].

Knowledge ensembling. It is well-known that an ensemble of multiple networks generally yields better predictions than a single network in the ensemble. The ensembling technologies aim to generate robust supervision signals via aggregating models [42, 14, 12] or predictions [25, 26, 37, 43, 13]. Several attempts leveraged the spirit of knowledge ensembling in distillation tasks, dubbed "ensemble distillation" methods. For example, CRD [43] and MEAL [37] proposed to enhance the soft targets by ensembling the knowledge of multiple pre-trained teacher networks. KDCL [13] introduced to aggregate the information from multiple independent students, which are collabora-

tively training. The idea of knowledge ensembling can be not only applied in supervised tasks, but also employed in semi-supervised [25, 42] and unsupervised tasks [14, 12]. Despite a big success, we remark that existing ensembling techniques all require different networks or branches, which may be inapplicable in resource-limited environments.

Label refinery for ImageNet classification. ImageNet [4] is a widely-acknowledged dataset in computer vision. Although it could well benchmark the performance of image classification methods, some studies [1, 2, 36, 51] have observed that the manually annotated labels for ImageNet are incomplete. Specifically, ImageNet was annotated under a single-labeling policy, i.e., one label per image, however, there are generally multiple objects in a single image. To overcome the problem, state-of-the-art label refinery methods [1, 51] produced multi-labels by an auxiliary annotator. For instance, [1] introduced an iterative training scheme, i.e., the trained network acted as the annotator for the next generation training. [51] relabeled the dataset with a super-strong classifier, which was pre-trained on superscale datasets. Although they cleaned up the noisy labels to some extent, they heavily depended on the capacity of external networks and required much resources to train a strong annotator, which was inflexible.

The key advantages of our BAKE against existing self-distillation, ensemble distillation and label refinery methods are summarized in Table 1.

3. Method

3.1. Revisit of Knowledge Distillation

Knowledge distillation [20] can be considered as regularizing the training of the student network using soft targets that carry the "dark knowledge" of the teacher network.

The student network generally consists of a backbone encoder F and a classifier C to perform classification. For each training sample x, its logit vector is encoded as z = C(F(x)). The predictive probability vector p^{τ} can be obtained via a softmax function on the logits, *i.e.*, the probability of class k can be formulated as

$$\boldsymbol{p}^{\tau}(k) = \frac{\exp(\boldsymbol{z}_k/\tau)}{\sum_{i=1}^{K} \exp(\boldsymbol{z}_i/\tau)},$$
 (1)

where τ is a temperature hyper-parameter, and K is the number of total classes. Let $y \in \{1,\ldots,K\}$ denotes the ground truth label and q^{τ} is the soft target produced by the teacher network. The cross-entropy loss and the KL divergence between the predictions and soft targets are minimized jointly to train the student via

$$\mathcal{L}_x = -\log \boldsymbol{p}(y) + \lambda \cdot \tau^2 \cdot D_{\mathrm{KL}}(\boldsymbol{q}^{\tau} || \boldsymbol{p}^{\tau}), \qquad (2)$$

where p(y) denotes the probability normalized without a temperature, and λ weights the two terms.

Recent works [26, 37, 43, 13] found that ensembling diverse "dark knowledge" from multiple teachers or students can form better soft targets, leading to better final performance (see Figure 2 (a)&(b) for details). However, this strategy would increase much more computational and memory overhead to enable multiple networks or branches training. To tackle the challenge, we introduce batch knowledge ensembling in a single network via self-distillation, as illustrated in Figure 2 (c).

3.2. Batch Knowledge Ensembling

Rather than utilizing multiple pre-trained high-capacity teachers [37, 43] or collaboratively training students [13], we propose a novel self-knowledge ensembling solution by exploring how to ensemble knowledge of different samples in the same mini-batch with a single network, *i.e.*, the student network itself. Intuitively, samples with high visual similarities are expected to have more consistent predictions on their predicted class probabilities, regardless of their ground-truth labels. In our solution, similar samples' knowledge is systematically aggregated and ensembled to provide better soft targets.

Batch knowledge propagation and ensembling. We propose to propagate and ensemble knowledge among samples on-the-fly in terms of their feature similarities. Given a mini-batch of N samples and a network $F \circ C$ under training, we first estimate the samples' pairwise similarities by the dot product of their encoded representations with the current network. Such similarities can be stored in an affinity matrix $A \in \mathbb{R}^{N \times N}$ as

$$A(i,j) = \sigma(F(x_i))^{\top} \sigma(F(x_j)), \tag{3}$$

where $\sigma(\mathbf{f}) = \mathbf{f}/\|\mathbf{f}\|_2$ denotes the ℓ_2 -norm and i,j are the indices of samples in a batch. To avoid the self-knowledge reinforcement, we discard the diagonal entries from A by $A = A \odot (1-I)$, where I is an identity matrix and \odot denotes the element-wise multiplication. Subsequently, we normalize each row of the affinity matrix A so that $\sum_{j=1}^N \hat{A}(i,j) = 1$ for all i, while keeping the diagonal all zeros, i.e., $\hat{A}(i,i) = 0$. The normalization can be formulated as a softmax function over each row of the matrix A

$$\hat{A}(i,j) = \frac{\exp(A(i,j))}{\sum_{j \neq i} \exp(A(i,j))}, \ \forall i \in \{1,\dots,N\}.$$
 (4)

We denote the predicted probabilities of samples within a batch as $P^{\tau} = [\boldsymbol{p}_1^{\tau}, \dots, \boldsymbol{p}_N^{\tau}]^{\top} \in \mathbb{R}^{N \times K}$, which satisfy $\sum_{k=1}^K P^{\tau}(i,k) = 1, \forall i$. For the *i*-th sample in the minibatch, we would like to weightedly propagate and ensemble the other samples' predictions to create a better soft target for it based on the inter-sample affinities, which can be for-

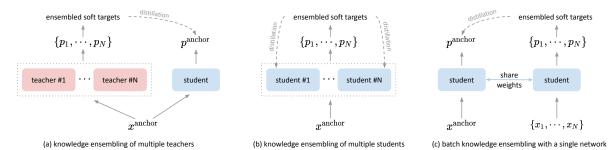


Figure 2. Conceptual comparison of three knowledge ensembling mechanisms. (a) **Multi-teacher ensembling** [37, 43]: the soft targets are produced by ensembling the knowledge from multiple pre-trained high-capacity teachers. (b) **Multi-student ensembling** [13]: the soft targets are refined by ensembling the knowledge from multiple peer-teaching students. (c) **The proposed BAKE**: generating robust soft targets by ensembling the knowledge of the other samples (i.e., $\{x_1, \dots, x_N\}$) in the same mini-batch. BAKE enables knowledge ensembling with a single network, saving the memory and time costs to a large extent.

mulated as

$$\hat{\boldsymbol{p}}_i^{\tau} = \sum_{j \neq i} \hat{A}(i, j) \boldsymbol{p}_j^{\tau} = \hat{A}(i) P^{\tau}, \tag{5}$$

where \hat{p}_i^{τ} is the propagated probability vector for the *i*-th sample and can serve as the refined soft targets. Intuitively, if the *i*-th sample and the *j*-th sample are similar with a high affinity $\hat{A}(i,j)$, the prediction p_j^{τ} would have a larger weight to be propagated to \hat{p}_i^{τ} . Propagating the predictions between all the samples in a mini-batch in parallel can be formulated as $\hat{P}^{\tau} = \hat{A}P^{\tau}$.

To avoid propagating and ensembling noisy predictions too much, we produce the soft learning targets Q^{τ} as a weighted sum of the initial probability matrix P^{τ} and the propagated one $\hat{A}P^{\tau}$,

$$Q^{\tau} = \omega \hat{A} P^{\tau} + (1 - \omega) P^{\tau}, \tag{6}$$

where $\omega \in [0,1]$ is the weighting factor and $Q^{\tau} = [\boldsymbol{q}_1^{\tau},\dots,\boldsymbol{q}_N^{\tau}]^{\top} \in \mathbb{R}^{N \times K}$. With the above formulations, the knowledge of the samples within the same batch can be propagated to each other and ensembled for one iteration.

Approximate inference. The knowledge propagation and ensembling can be conducted for multiple times until convergence for fully fusing their knowledge

$$\begin{split} Q_{(t)}^{\tau} &= \omega \hat{A} Q_{(t-1)}^{\tau} + (1 - \omega) P^{\tau} \\ &= (\omega \hat{A})^{t} P^{\tau} + (1 - \omega) \sum_{i=0}^{t-1} (\omega \hat{A})^{i} P^{\tau}, \end{split} \tag{7}$$

where t denotes the t-th propagation and ensembling iteration. When the number of iterations approaches infinite, we have $\lim_{t\to\infty} (\omega \hat{A})^t = 0$, given that $\omega \in [0,1]$. Also, since

$$\lim_{t \to \infty} \sum_{i=0}^{t-1} (\omega \hat{A})^i = (I - \omega \hat{A})^{-1}, \tag{8}$$

where I is an identity matrix. We can obtain an approximate inference formulation for the knowledge propagation and ensembling as

$$Q_{(\infty)}^{\tau} = (1 - \omega)(I - \omega \hat{A})^{-1} P^{\tau}.$$
 (9)

Note that $Q_{(\infty)}^{\tau}$ naturally satisfies $\sum_{k=1}^{K} Q_{(\infty)}^{\tau}(i,k) = 1$ for all i without requiring extra normalization, which forms valid soft targets for training. The gradient is not backpropagated through the soft targets $Q_{(\infty)}^{\tau}$ for stable training.

For each training sample, we estimate its soft targets $q_{(\infty)}^{\tau} \in Q_{(\infty)}^{\tau}$ by ensembling the knowledge from other samples in the same batch with the approximate inference formula (Eq. (9)). The produced $q_{(\infty)}^{\tau}$ is then used as a refined learning target to supervise the self-distillation procedure with Eq. (2). The overall training procedure is detailed in Algorithm 1.

3.3. Discussion

Time and memory consumption. BAKE generates refined soft targets on-the-fly with *minimal* computational and memory overhead compared to existing ensemble distillation methods. BAKE does not need additional network parameters on top of ordinary backbones (*e.g.*, [26]), and does not require auxiliary networks (*e.g.*, multiple student networks for peer teaching [13]). Only very few additional GPU memory (+2.2% for ResNet-50) is required for prediction propagation and ensembling in addition to the conventional classification loss. Furthermore, BAKE does not require pre-trained teachers or annotators (*e.g.*, [43, 37]). Only little additional training time (+3.7% for ResNet-50) is required for ensembling the knowledge within each batch and optimizing the network via the self-distillation loss.

Data sampling. BAKE propagates and ensembles the knowledge based on inter-sample affinities. In the experiments, we found that BAKE does not work if the samples in a mini-batch are totally dissimilar to each other, *i.e.*, showing uniformly low affinities. To ensure that similar pairs

Algorithm 1: PyTorch-style pseudocode for BAKE.

```
w: ensembling weight
     temperature
    loss weight
for (x, gt_labels) in loader:
    # features: N×D, logits:
    f, logits = net.forward(x)
    # classification loss with ground-truth labels
   loss = CrossEntropyLoss(logits, gt_labels)
    # produce soft targets
   f = normalize(f)
   A = softmax(mm(f, f.t())-eye(N)*1e-9) # row-wise
 normalization of affinity matrix with zero
 diagonal
   soft_targets = mm((1-w) \cdot inv(eve(N) - w \cdot A),
 softmax(logits/t)) # approximate inference for
 propagation and ensembling
   soft_targets = soft_targets.detach() # no
 gradient.
    # distillation loss with soft targets
   loss += KLDivLoss(log_softmax(logits/t),
 soft_targets) *t2 *r
    # SGD update
   loss.backward()
   update(net.params)
```

mm: matrix multiplication; eye: identity matrix; inv: inverse matrix.

can always be found in the mini-batch, we introduce a perclass data sampler on top of the common random sampling mechanism. Specifically, for an anchor image in a randomly sampled mini-batch, we randomly select another M images out of the same class. Given the initial batch size of \hat{N} and M intra-class images for each anchor, we would have a total batch size of $\hat{N}=\hat{N}\times(M+1)$ for training. For example, we use $\hat{N}=256$ and M=1 for our experiments on ImageNet, yielding a batch size of N=512.

4. Experiments

4.1. Experimental Details

Datasets. We study the effectiveness of BAKE mainly on the large-scale ImageNet-1K [4] (ILSVRC2012), which is considered as one of the most important benchmarks in learning visual representations. We also evaluate BAKE on the other two conventional image classification datasets, CIFAR-100 [24] and TinyImageNet*, and three fine-grained image classification datasets, CUB-200-2011 [45], Stanford Dogs [23] and MIT67 [32]. The statistics of datasets can be found in Table 2. Top-1 and top-5 classification accuracies are calculated for evaluation.

Network architectures. To demonstrate that our BAKE can consistently improve various architectures on multiple datasets, we study the family of ResNets, including ResNet [16], ResNeSt [53] and ResNeXt [47], and the lightweight

Dataset	# classes	# train images	# val images
ImageNet [4]	1,000	1,281,167	50,000
CIFAR-100 [24]	100	50,000	10,000
TinyImageNet	200	100,000	10,000
CUB-200-2011 [45]	200	5,994	5,794
Stanford Dogs [23]	120	12,000	8,580
MIT67 [32]	67	5,360	1,340

Table 2. Statistics of the datasets used for training and evaluation.

networks, including MobileNet-V2 [35] and EfficientNet-B0 [41], on the ImageNet benchmark. We also evaluate ResNet [16] and DenseNet [21] on the other relatively smaller scale datasets. Note that we use the pre-activation blocks [17] for CIFAR-100 and TinyImageNet datasets following the setup in [52].

4.2. ImageNet Classification

Training details. There are three hyper-parameters required by the training of BAKE. In the loss function Eq. (2), we set the distillation loss weight λ as 1.0 and the temperature τ as 4.0. In the approximate inference function Eq. (9) of knowledge ensembling, we set the ensembling weight ω as 0.5. BAKE is not sensitive to these hyper-parameters, which will be discussed next.

We implement our BAKE on top of the open-source codebase[†], and follow most of the training settings of [33]. Specifically, we use SGD as our optimizer with a momentum of 0.9. We use standard augmentation techniques including random cropping, flipping, and lighting noise. All the images are resized to 224×224 for training and 256×256 for validation. The batch size is set to 512, *i.e.*, $\hat{N} = 256$ for the initial random sampling and M = 1 for the per-class data sampling (see Section 3.3). The base learning rate is set as 0.05 for MobileNet, 0.2 for the family of ResNets and 0.4 for EfficientNet. The initial learning rate is calculated via $lr = base_lr \times batch_size/256$. We use cosine schedule with 5-epoch warm-up as the learning rate policy. All the experiments are trained for 100 epochs on 8 GPUs if not specified.

Improvements on various architectures. As illustrated in Table 3, we verify the effectiveness of BAKE on multiple network architectures. We not only consider the widely-used architectures (*e.g.*, ResNet-50), but also evaluate both the deeper/wider architectures (*e.g.*, ResNet-152, ResNeXt-152) and the lighter architectures (*e.g.*, MobileNet). BAKE consistently improves the "vanilla" setting (training with a cross-entropy loss) by significant margins. Most importantly, BAKE boosts the performance with only negligible computational overhead, *i.e.*, for each training iteration of ResNet-50, BAKE takes only extra +3.7% more time compared to the plain classification network.

^{*}https://tiny-imagenet.herokuapp.com

[†]https://github.com/facebookresearch/pycls

Architecture	N Vanilla	fethod Our BAKE	GPU Time
ResNet-50	76.8	78.0 (+1.2)	+3.7%
ResNet-101	78.6	79.3 (+0.7)	+2.1%
ResNet-152	79.1	79.6 (+0.5)	+1.1%
ResNeSt-50	78.4	79.4 (+1.0)	+2.8%
ResNeSt-101	79.6	80.4 (+0.8)	+1.3%
ResNeXt-101 (32x4d)	78.7	79.3 (+0.6)	+1.9%
ResNeXt-152 (32x4d)	79.3	79.7 (+0.4)	+1.7%
MobileNet-V2	71.3	72.0 (+0.7)	+1.5%
EfficientNet-B0	75.1	76.2 (+1.1)	+6.8%

Table 3. BAKE improves various architectures with minimal computational overhead. We report the top-1 accuracy (%) on ImageNet. "Vanilla" indicates training with a conventional crossentropy loss. The time consumption is counted on 8 Titan X GPUs.

Method		ImageNet		
		top-1 acc.	top-5 acc.	
Vanilla ResNet-50		76.8	93.4	
Label smoothing [40]	CVPR'16	77.2	93.7	
$Tf\text{-}KD_{reg}$ [49]	CVPR'20	77.5	93.7	
BAN [5]	ICML'18	77.4	93.5	
CS-KD [52]	CVPR'20	77.0	93.4	
Tf-KD $_{self}$ [49] CVPR'20		77.5	93.7	
Our BAKE		78.0	94.0	

Table 4. Comparison with state-of-the-art label regularization and self-distillation methods, both of which are based on single networks. We report the results of ResNet-50 on the ImageNet. All the methods are reproduced on our implementation with identical training settings as BAKE for fair comparisons and their performances surpass the reported results in their original papers.

Comparison with label regularization methods. As mentioned by [49], label smoothing regularization is an ad hoc distillation with manually designed soft targets. To indicate that the ensembled soft targets by BAKE are better roles than the ad hoc regularizations, we evaluate both conventional label smoothing [40] regularization and the newly proposed teacher-free Tf-KD $_{reg}$ [49] regularization based on the ResNet-50 classification backbone network, respectively. As shown in Table 4, the above mentioned label regularization methods can improve the "vanilla" network with satisfactory margins, but still show inferior performance than our proposed BAKE. For instance, the state-of-the-art Tf-KD $_{reg}$ improves the "vanilla" by 0.7% in terms of top-1 accuracy but is still -0.5% lower than our BAKE.

Comparison with self-distillation methods. Our BAKE can be categorized into self-distillation methods, *i.e.*, regularizing the network predictions using its own knowledge. State-of-the-art self-distillation methods only considered the knowledge of individual samples [5, 49] or pairwise samples [52], producing inferior soft targets than our

Method	Epochs	Top-1 acc.	Extra Params
MEAL [37]	180	78.2	ResNet-101 & 152
KDCL [13]	200	77.8	ResNet-18
Our BAKE	100	78.0	/

Table 5. Comparison with state-of-the-art ensemble distillation methods. We report the results of ResNet-50 on the ImageNet. The results of MEAL and KDCL are from the original papers. CRD [43] did not report on ResNet-50, thus is not compared here. CRD, MEAL and KDCL require extra networks, while BAKE does not.

BAKE. To verify it, we reproduce these methods on top of our implementation and achieve better performances than the performances reported in their original papers (see Table 4). There remains an obvious performance gap between their methods and our BAKE, e.g., BAKE surpasses CS-KD [52] by 1.0% and Tf-KD_{self} [49] by 0.5% in terms of top-1 accuracy.

Comparison with ensemble distillation methods. Our BAKE is designed following the spirit of knowledge ensembling, which aims to refine the soft targets by aggregating diverse and complementary knowledge. State-of-the-art ensemble distillation methods achieved knowledge ensembling by leveraging multiple teachers [37, 43] or multiple students [13], which are illustrated in Figure 2. We argue that our BAKE could not only save the memory and time consumption by enabling knowledge ensembling in a single network, but also generate equally robust soft targets by aggregating knowledge from a set of samples in the same mini-batch. To demonstrate it, we compare state-of-the-art MEAL [37] and KDCL [13] in Table 5. We observe that our BAKE achieves similar results by using a single network for much fewer training epochs. BAKE even beats KDCL with half of the training epochs, where KDCL requires an extra ResNet-18 for ensembling.

Comparison with label refinery methods. Recent studies on improving ImageNet classification found that the single labels are noisy as there might exist multiple objects per image. State-of-the-art ReLabel [51] method introduced to use a super-strong EfficientNet-L2 for re-labelling the ImageNet with multiple labels in the image spatial plane. However, it requires super-scale datasets (much larger than ImageNet) and much more time and memory consumption to pre-train an annotator network first, which is inflexible and even inapplicable if we do not have such resources. Even so, we are glad to find that our BAKE can surpass the ReLabel method by using only ImageNet dataset with the ResNet-50 backbone. As the original ReLabel was trained for 300 epochs, we reproduce it with their official code for 100 epochs to fairly compare with BAKE. As shown in Table 6, ReLabel achieves 77.3% top-1 accuracy when trained for 100 epochs, showing much lower performance than our BAKE's 78.0%. BAKE is also well compatible with exter-

Method	Epochs	Top-1 acc.	Extra Params
ResNet-50	100	76.8	/
+ ReLabel [51]	100	77.3	EffNet-L2
+ Our BAKE	100	78.0	/
ResNet-50 + CutMix [50]	100	77.4	/
+ ReLabel [51]	100	78.4	EffNet-L2
+ Our BAKE	100	78.6	/

Table 6. Comparison with state-of-the-art label refinery method on ImageNet. The results of ReLabel for 100 epochs are reproduced with the official code. ReLabel [51] requires a strong annotator network (EfficientNet-L2 [41]) pre-trained on super-scale datasets (JFT-300M [38] or Instagram-1B [30]) for re-labelling, while BAKE does not.

	Faster-RCNN Mask		-RCNN	
	bbox mAP	bbox mAP	mask mAP	
ResNet-50	37.7	38.5	35.0	
+ Our BAKE	38.3 (+0.6)	39.2 (+0.7)	35.5 (+0.5)	

Table 7. Transfer learning performances for object detection and instance segmentation on the COCO dataset [28]. ResNet-50 is adopted as the backbone.

nal training tricks, e.g., CutMix [50]. BAKE consistently improves the baseline performance by noticeable +1.2% (77.4% \rightarrow 78.6%) when trained for 100 epochs with CutMix. "BAKE + CutMix" also consistently surpasses "ReLabel + CutMix" by a +0.2% gain.

Transfer learning. Apart from performing the classification task, the models trained on ImageNet can also be well transferred to the downstream tasks by fine-tuning. To show that the ImageNet pre-trained model by BAKE could achieve better transfer learning results, we evaluate two important downstream tasks on the COCO [28] dataset. As demonstrated in Table 7, we use Faster-RCNN [34] and Mask-RCNN [15] with feature pyramid network [27] as base models for object detection and instance segmentation, respectively. The experiments are conducted on top of the open-source codebase ‡ . The baseline results (e.g., 37.7% mAP for detection) are achieved by fine-tuning the model pre-trained with the "vanilla" backbone (76.8% top-1 accuracy for classification). We observe that the model pre-trained by BAKE (78.0% top-1 accuracy for classification) could consistently improve the baseline results by $0.5\% \sim 0.7\%$ in terms of mAP.

Robustness testing. Our BAKE does not only improve image classification, but also improves the classification robustness on much harder test sets with either common perturbations or adversarial perturbations. ImageNet-A [19] contains difficult testing images sampled from the failure cases of modern classifiers. ImageNet-C [18] consists of 19 different corruptions and perturbations, *e.g.*, blurring, fog-

	ImageNet top-1 acc. ↑	ImageNet-A top-1 acc. ↑	ImageNet-C mCE ↓
ResNet-50	76.8	2.7	57.9
+ Our BAKE	78.0 (+1.2)	4.6 (+1.9)	57.4 (-0.5)

Table 8. Robustness on ImageNet-A [19] and ImageNet-C [18] test sets. Note that mCE is the weighted average of top-1 error rates with different corruptions (lower is better).

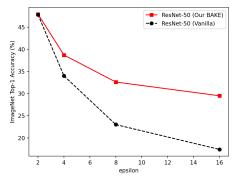


Figure 3. Our BAKE improves adversarial robustness against the FGSM [11] attack. The improvements are more significant as ϵ increases. The results are reported based on ResNet-50.

ging. As indicated in Table 8, BAKE successfully improves the robustness of the trained models against natural perturbations. FGSM [11] imposes one-step adversarial perturbations on the input image with a weight of ϵ . As shown in Figure 3, at $\epsilon=16$, BAKE significantly improves ResNet-50's accuracy from 17.4% to 29.5% though the model is not optimized for adversarial robustness.

Ablation studies on per-class data sampling. As described in Section 3.3, we adopt a per-class data sampling strategy to ensure that the sample affinities are not uniformly low in a mini-batch. We would like to claim that (1) The per-class data sampling strategy is critical to the success of BAKE. BAKE would fail when a conventional random sampling scheme is used. (2) The gains of BAKE derive from the refined soft targets by ensembled knowledge rather than the data sampling strategies.

To demonstrate our first claim, we conduct experiments when removing the proposed per-class sampling strategy. As shown in Table 9, we use "M=0" to indicate the conventional random sampling without per-class selection, and we observe that BAKE hardly improves the baseline performances. When adopting the introduced per-class sampling with M=1 or M=3, BAKE stably boosts the baseline results by up to +1.8% gains. As BAKE achieves similar improvements when M>0, we set M as 1 for brevity.

To further verify the second claim, we evaluate "vanilla" when using different values of M. From Table 9, we observe that the performance of "vanilla" settings would decrease when using M>0, indicating that the per-class sampling would even hurt the model training if not used

[†]https://github.com/open-mmlab/mmdetection

Method	M	\hat{N}	# Batch	ImageNet top-1 acc.
ResNet-50 + Our BAKE	0	256 256	256 256	76.8 76.8 (+0.0)
ResNet-50	1	256	512	76.3
+ Our BAKE	1	256	512	78.0 (+1.7)
ResNet-50	3	256	1024	76.1
+ Our BAKE		256	1024	77.9 (+1.8)

Table 9. Ablation studies on the value of M in the per-class data sampling scheme, where batch_size $= \hat{N} \times (M+1)$.

Soft targets	ω	ImageNet top-1 acc.
Equal to raw predictions	0.0	76.3
Refined by BAKE	0.1	77.7
Refined by BAKE	0.3	77.8
Refined by BAKE	0.5	78.0
Refined by BAKE	0.7	77.8
Refined by BAKE	0.9	78.0
All zeros	1.0	fail

Table 10. Ablation studies on the value of the ensembling weight ω in Eq. (9). We report the results of ResNet-50 on the ImageNet.

Soft targets	au	Top-1 acc.	Weight λ	Top-1 acc.
Original Smoothed by 2× Smoothed by 4× Smoothed by 8×	1.0 2.0 4.0 8.0	77.9 78.0 78.0 77.8	0.5 1.0 2.0 3.0 4.0	77.8 78.0 78.0 78.0

Table 11. Ablation studies on the value of the temperature τ and the value of the weighting factor λ in Eq. (2). We report the results of ResNet-50 on the ImageNet.

with BAKE. The reason might be that the per-class data sampling actually decreases the data variations within each batch. As the "vanilla" experiment achieves the optimal performance when M=0, we do not use the per-class sampling for all the "vanilla" experiments throughout the paper.

Ablation studies on the ensembling weight ω . The ensembling weight $\omega \in [0,1]$ is adopted to weigh the original knowledge of the anchor sample and the propagated knowledge of other samples within the same batch, as formulated in Eq. (9). The refined soft targets $Q_{(\infty)}^{\tau}$ ensemble more knowledge from the other samples as ω gets larger. As shown in Table 10, when ω approaches 0, the soft targets is equal to the vanilla predictions of the anchor sample, i.e., $Q_{(\infty)}^{\tau} = P^{\tau}$, the distillation loss then becomes useless. When ω approaches 1, the soft targets become all zeros and BAKE fails. The performance of BAKE is robust when changing the value of ω within a large interval of [0.1, 0.9].

Ablation studies on the temperature τ . The temperature τ is adopted to scale the predicted logits and the soft targets in the distillation loss (Eq. (2)). A higher value of τ leads to a smoother probability distribution over classes. As illustrated in Table 11, we study the effects of the temperature

value on BAKE by changing τ from 1.0 to 8.0. We observe that BAKE is not sensitive to the temperature and achieves robust results.

Ablation studies on the weighting factor λ . λ is adopted to balance the cross-entropy loss and the knowledge distillation term in Eq. (2), which is normally set to 1.0 for brevity. We are interested in how much it affects the final performance. As demonstrated in Table 11, the performance is consistent when changing λ from 1.0 to 3.0, and is robust in the interval of [0.5, 4.0].

4.3. Small-scale Dataset Classification

Training details. We adopt almost the same settings as those used for training the ImageNet. We use $\lambda=1.0$ and $\tau=4.0$ for Eq. (2). The ensembling weight ω (Eq. (9)) is chosen from $\{0.5,0.9\}$, according to the results in Table 10. M is chosen from $\{1,3\}$, according to the results in Table 9. The experiments are implemented on top of the open-source code§. Specifically, we use SGD as our optimizer with a momentum of 0.9. The batch size is set to 128 for CIFAR-100 and TinyImageNet, and set to 32 for the fine-grained classification datasets. The initial learning rate is set to 0.1 and is decreased to 1/10 of its previous value at the 100-th and 150-th epoch in the overall 200 training epochs. All the experiments are trained with only 1 GPU.

Improvements on various architectures and datasets. As shown in Table 12, we study the effectiveness of BAKE with a lightweight ResNet-18 and a deep DenseNet-121 on multiple classification datasets. BAKE consistently improves the baseline results ("vanilla") by significant margins, *e.g.*, on the fine-grained dataset CUB-200-2011, BAKE boosts the baseline by 16.26% with ResNet-18. Also, on the widely-used CIFAR-100 dataset, the performance of ResNet-18 is improved by 3.43% by BAKE.

Comparison with self-distillation methods. Following the benchmark used by [52], we compare with state-of-the-art self-distillation methods, DDGSD [48], BYOT [54] and CS-KD [52]. BAKE stably surpasses all the methods except for the experiments of ResNet-18 on TinyImageNet, which shows a slight drop from DDGSD [48]. The positive results of BAKE are enough to demonstrate its effectiveness and superiority over existing self-distillation methods.

5. Conclusions and Discussions

In this work, we introduce a novel batch knowledge ensembling method, dubbed BAKE, to produce refined soft targets for self-distillation. Rather than aggregating multiple networks or branches, BAKE is proposed to weightedly propagate and ensemble the knowledge from different samples in the same mini-batch. BAKE improves the image

[§]https://github.com/alinlab/cs-kd

Architecture	Method		CIFAR-100 [24]	TinyImageNet	CUB-200-2011 [45]	Stanford Dogs [23]	MIT67 [32]
	Vanilla		$24.71_{\pm0.24}$	$43.53_{\pm0.19}$	$46.00_{\pm 1.43}$	$36.29_{\pm0.32}$	$44.75_{\pm0.80}$
ResNet-18	Label smoothing [40] DDGSD [48] BYOT [54] CS-KD [52]	CVPR'16 AAAI'19 ICCV'19 CVPR'20	$\begin{array}{c} 22.69_{\pm 0.28} \\ 23.85_{\pm 1.57} \\ 23.81_{\pm 0.11} \\ 21.99_{\pm 0.13} \end{array}$	$43.09_{\pm 0.34} \\ 41.48_{\pm 0.12} \\ 44.02_{\pm 0.57} \\ 41.62_{\pm 0.38}$	$\begin{array}{c} 42.99_{\pm 0.99} \\ 41.17_{\pm 1.28} \\ 40.76_{\pm 0.39} \\ 33.28_{\pm 0.99} \end{array}$	$35.30_{\pm 0.66}$ $31.53_{\pm 0.54}$ $34.02_{\pm 0.14}$ $30.85_{\pm 0.28}$	$\begin{array}{c} 44.40_{\pm 0.71} \\ 41.17_{\pm 2.46} \\ 44.88_{\pm 0.46} \\ 40.45_{\pm 0.45} \end{array}$
	Our BAKE		$21.28_{\pm0.15}$	$41.71_{\pm0.21}$	$29.74_{\pm0.70}$	$30.20_{\pm0.11}$	$39.95_{\pm0.20}$
	Vanilla		$22.23_{\pm 0.04}$	$39.22_{\pm0.27}$	$42.30_{\pm0.44}$	$33.39_{\pm0.17}$	$41.79_{\pm0.19}$
DenseNet-121	Label smoothing [40] CS-KD [52]	CVPR'16 CVPR'20	$21.88_{\pm 0.45} \\ 21.69_{\pm 0.49}$	$38.75_{\pm0.18} \ 37.96_{\pm0.09}$	$40.63_{\pm 0.24}\atop30.83_{\pm 0.39}$	$31.39_{\pm 0.46} $ $27.81_{\pm 0.13}$	$\substack{42.24_{\pm 1.23}\\40.02_{\pm 0.91}}$
	Our BAKE	-	$20.74_{\pm0.19}$	$37.07_{\pm0.24}$	$28.79_{\pm 1.30}$	$27.66_{\pm0.05}$	$39.15_{\pm0.37}$

Table 12. Top-1 error rates (lower is better) on multiple image classification and fine-grained classification tasks. The performances of state-of-the-art single-network methods (*i.e.*, label regularization methods and self-distillation methods) are reported for comparison. All the experiments are run for three times with different random seeds.

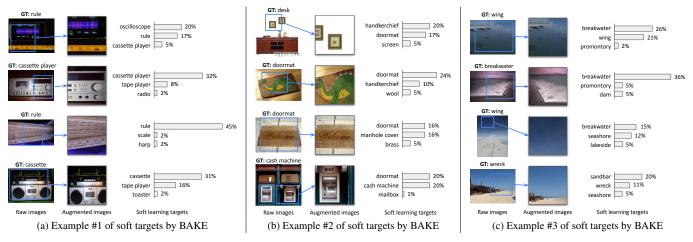


Figure 4. We sample three tuples of images (four images in each tuple) from three batches to show the soft targets produced by BAKE. The images are sampled from ImageNet [4]. "GT" denotes the manually annotated ground-truth labels. The knowledge of samples from the same batch is propagated and ensembled to form a better soft learning target for each sample in the batch. Note that only the top-3 classes of soft targets with the highest probabilities are illustrated for brevity.

classification performance with minimal computational and memory overhead, and outperforms state-of-the-art singlenetwork methods on all the tested benchmarks.

Beyond the classification tasks, the spirit of batch knowledge ensembling has great potential on other tasks, *e.g.*, image retrieval, segmentation and detection. Furthermore, it may also be interesting to explore the batch knowledge in modern self-supervised learning frameworks (*e.g.*, [14, 3, 12]), as the batch knowledge ensembling is based on the sample affinities regardless of their ground-truth labels.

A. Appendix

A.1. Examples of Soft Targets by BAKE

We illustrate the examples of soft targets produced by BAKE in Figure 4. We sample the images from three different batches, where the cross-sample knowledge propagation and ensembling are performed in each mini-batch. There are 512 images included in each batch, and we randomly

select four of them for illustration. We present their ground-truth labels as well as the soft labels generated by BAKE. The soft label is a 1000-dim probability vector (1000 classes for ImageNet), and we only show the probabilities of top-3 classes for brevity. It can be observed that the soft targets produced by BAKE provide more informative and complete training supervisions than the manual annotations.

A.2. Additional Ablation Studies

Ablation studies on the batch knowledge ensembling iterations. We adopt approximate inference to estimate the soft targets for infinite ensembling iterations. To indicate that infinite iterations achieve better learning targets than a single iteration, we conduct experiments as shown in Figure 5. Specifically, "BAKE with $Q_{(\infty)}^{\tau}$ " produces soft targets via approximate inference for infinite iterations (Eq. (9)) and "BAKE with Q^{τ} " adopts only one iteration for ensembling (Eq. (6)). We can observe that "BAKE with $Q_{(\infty)}^{\tau}$ " achieves more robust results than "BAKE with Q^{τ} " when

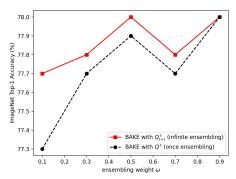


Figure 5. Our BAKE achieves more robust results when ensembling batch knowledge for infinite iterations. The results are reported based on ResNet-50.

Method	Type of BN	ImageNet top-1 acc.
Vanilla	Normal BN Sync BN	76.8 76.7
Our BAKE	Normal BN Sync BN Shuffling BN [14]	74.7 78.0 78.1

Table 13. Ablation studies on the usage of BN when employing distributed training. We report the results of ResNet-50 on the ImageNet.

Method	Epochs	ImageNet top-1 acc.
Our BAKE + CutMix [50]	100 200 300	78.6 79.0 79.4

Table 14. Results of BAKE for different training epochs. We report the results of ResNet-50 on the ImageNet.

changing the ensembling weight ω from 0.1 to 0.9.

Ablation studies on BN for distributed training. We adopt the per-class data sampler when training BAKE, as introduced in Section 3.3. We find that the usage of BN is critical to final performance when employing distributed training, since the per-class data sampler decreases the data variations within each mini-batch on a single GPU. As demonstrated in Table 13, sync BN and shuffling BN [14] both work for the per-class data sampler, while using normal BN achieves even worse performance than the baseline result (76.8%). We choose sync BN in our paper due to its more efficiency. Using normal BN or sync BN achieves similar performance ($\pm 0.1\%$) when training the baseline without per-class data sampling, indicating that the gains of BAKE comes from the knowledge ensembling rather than the sync/shuffling BN. Note that experiments using the perclass data sampling throughout the paper adopt sync BN during training.

Different training epochs of BAKE. To investigate the performance of BAKE when training for different epochs, we conduct comparison experiments as demonstrated in Ta-

ble 14. All the experimental settings except the training epochs are kept the same. We observe that the results of "BAKE + CutMix" can be consistently boosted by training with more epochs.

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