Efficient Knowledge Distillation from Model Checkpoints

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Abstract

Knowledge distillation is an effective approach to learn compact models (students) with the supervision of large and strong models (teachers). As empirically there exists a strong correlation between the performance of teacher and student models, it is commonly believed that a high performing teacher is preferred. Consequently, practitioners tend to use a well trained network or an ensemble of them as the teacher. In this paper, we observe that an intermediate model, *i.e.*, a checkpoint in the middle of the training procedure, often serves as a better teacher compared to the fully converged model, although the former has much lower accuracy. More surprisingly, a weak snapshot ensemble of several intermediate models from a same training trajectory can outperform a strong ensemble of independently trained and fully converged models, when they are used as teachers. We show that this phenomenon can be partially explained by the information bottleneck principle: the feature representations of intermediate models can have higher mutual information regarding the input, and thus contain more "dark knowledge" for effective distillation. We further propose an optimal intermediate teacher selection algorithm based on maximizing the total task-related mutual information. Experiments verify its effectiveness and applicability. Our code is available at https://github.com/LeapLabTHU/CheckpointKD.

1 Introduction

Knowledge distillation (KD) [1, 2] has been proved to be an effective technique to promote the performance of a low-capacity model by transferring "dark knowledge" from a large teacher model. Empirically, there usually exists a strong correlation between the performance of the teacher model and the student model. For this reason, it is a standard practice to use a well trained network or an ensemble of multiple well trained networks as the teacher [3, 4, 5], and some researches are attempted to improve distillation performance via boosting the ensemble performance [6, 7]. The underlying assumption is that high performing teachers lead to better student models.

However, this viewpoint has been challenged by some recent works [8, 9, 10, 11, 12], in which it has been observed that a large model capacity gap between the teacher and student may have a negative effect for knowledge transfer. To address this issue, researchers have proposed to employ an intermediate-size network [8] or an assistant network [9] to improve the distillation performance in such scenarios. In [10], a "tolerant" teacher model is designed by using a softened loss function. In [11], Park et al. proposed to learn student-friendly teacher by plugging in student branches during the training procedure. Nevertheless, there is no clear theoretical explanation for the gap between teacher and student, and the search for a substitute teacher is not straightforward.

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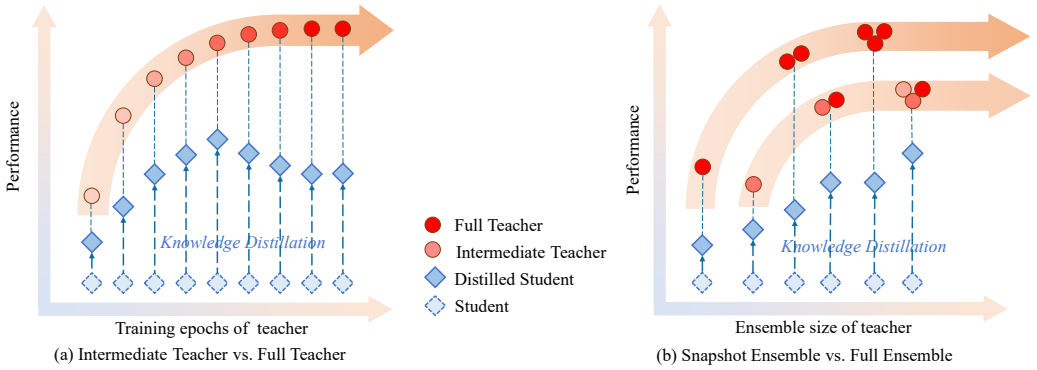

Figure 1: A sketch map of the two counterintuitive observations. (a) A weak intermediate model can serve as a better teacher than the strong fully converged model. (b) A weak Snapshot Ensemble [13] can serve as a better teacher than the strong Full Ensemble.

In this paper, we make an intriguing observation that further supports the viewpoint that *high performing models may not necessarily be good teachers*, but from a novel perspective. Specifically, we find that an unconverged intermediate model from the middle of the training procedure, often serves as a better teacher than the final converged model, although the former has much lower accuracy (as illustrated in Figure 1(a)) . Moreover, a weak snapshot ensemble of intermediate teacher models along the same optimization path (denoted as Snapshot Ensemble, which is a variant of [13][3]) can outperform the standard ensemble of an equal number of independently trained teacher models (denoted as Full Ensemble). This surprising phenomenon is illustrated in Figure 1(b), in which a Snapshot Ensemble can have better distillation performance than a Full Ensemble, although the accuracy of the former is significantly lower.

To understand the above phenomenon, we show that there is a strong connection between KD and the information bottleneck (IB) theory [14]. Therein, it has been observed that during the training procedure of deep neural networks, the mutual information between the learned features F and the target Y, denoted as $I(Y;F)$, increases monotonically as a function of the training epochs; while the mutual information between F and the input X, denoted as $I(X;F)$, grows in the early training stage, but then decreases gradually after a certain number of epochs. We note that maximizing the mutual information $I(Y;F)$ is helpful for improving the teacher model itself, but not always necessary for KD, because the ground truth target Y is already included in the KD objective function. In contrast, the mutual information $I(X;F)$, to some extent, can be viewed as a type of dark knowledge that is desired for effective KD. For example, considering an image with a man driving a car, although it may be uniquely labeled into the "car" category, it still contains features of the "people" category. Such weak but non-negligible features extracted from the input (measured by $I(X;F)$) are in fact the knowledge that are most valuable for training student models. Not surprisingly, most KD algorithms apply a high temperature to soften the network prediction in order to reveal these information from a teacher model. However, as shown by IB theory, a fully converged model tends to be overconfident and may already have collapsed representations for non-targeted classes. Therefore, simply scaling the temperature can not effectively recover the suppressed knowledge. On the contrary, an intermediate model, although does not reach its top accuracy due to non-optimal $I(Y;F)$, may have a larger $I(X;F)$ that benefits KD. This partially explains our observation that intermediate models can be better teachers. More detailed and formal analyses are provided in the following sections.

Further, we propose an optimal intermediate teacher selection algorithm based on the IB theory. From the perspective of entropy, the teacher model's representation can be decomposed as the information with respect to the input, the output and some nuisance [15]. The proposed algorithm aims to find the most informative intermediate teacher model which possesses the minimal part of nuisance on a training trajectory. Experiments verify its applicability in various distillation scenarios. Our contributions are summarized as follows:

- By designing two exploratory experiments, we observe the phenomenon that intermediate models can serve as better teachers than fully converged models. This suggests that for

[3]In this paper,we adopt a normal cosine learning rate instead of the cyclic learning rate.

effective KD one should not only focus on improving the teacher performance. Instead, rethinking what the "dark knowledge" is and how to enrich it is highly valuable.

- We demonstrate the connection between our observations and the IB theory, providing a new perspective for understanding KD and explaining the "dark knowledge".
- Based on our observations and analyses, a novel simple but effective algorithm is proposed to find the optimal intermediate teacher and achieve better distillation performance. Experiments validate its effectiveness and adaptability.

2 Related Work

Knowledge distillation. Hinton et al. [2] proposed to transfer "dark knowledge" of a strong capacity teacher model to a compact student model by minimizing the Kullback-Leibler divergence between the soft targets of the two models. Since then, many variants of KD methods were proposed to improve the distillation performance[16], such as Fitnets [17], AT[18], CCM[19], FSP[20], SP[21], CCKD[22],TC^{3}KD[23]. As a promising technique to improve model generalization, ensemble learning is often combined with knowledge distillation to improve the distillation performance[3, 11, 4]. In the online knowledge distillation framework[24], efforts were made to boost the distillation performance by increasing the diversity between multiple models to improve the ensemble performance [6, 7]. Most existing methods commonly assumed that a high performing teacher is preferred for KD. On the contrary, some researchers thought that the model capacity gap between strong teachers and small students usually degrades knowledge transfer[8, 9, 12, 25]. Some of them have experimentally verified that poor teachers can also perform KD tasks well[12, 25]. Several methods are proposed to compress this gap by introducing an assistant network [8, 9] or designing a student-friendly teacher [10, 11]. However, they did not explain theoretically why gap exists and how gap affects KD. In the self-distillation framework[26, 27], it is essentially the intermediate model that is used as the teacher, but no one has a theoretical explanation for why the intermediate model works. In this paper, we link KD and IB theory through extensive observations and experiments. From the perspective of mutual information, we explain why intermediate models serve as better teachers than full models, and how to select an suitable intermediate model to reduce the negative impact of model gap.

Information bottleneck. Tishby et al. [28] firstly proposed the information bottleneck concept and provided a tabular method to numerically solve the IB Lagrangian (Eq. (3)). Later, Tishby and Zaslavsky [14] proposed to interpret deep learning with IB principle. Following this idea, Shwartz-Ziv and Tishby [29] studied the IB principle to explain the training dynamics of deep networks. It has motivated many studies to apply the IB principle to interpret and improve deep neural networks (DNNs) [30, 31, 32]. Recently, some researchers introduced IB principle to deep reinforcement learning successfully [33, 34, 35]. As far as we know, we are the first to introduce IB principle to interpret knowledge distillation.

3 Exploratory Experiments

In this section, we first formally describe the KD and ensemble KD methods used in the paper, then design two exploratory experiments to show how intermediate models are surprisingly valuable for KD, despite their lower accuracies due to incompletion of training.

3.1 Formulation

In the classical KD setting, a fully converged teacher model (full teacher for short) T^{full} is used to distill a student model S. Define $P_{\text{T}^{\text{full}}}$ as the softmax output of teacher model, P_{S} as the softmax output of student model and Y_{true} as the true labels. The student model is trained to optimize the following loss function:

$$L_{\text{KD}} = \alpha H(Y_{\text{true}}, P_{\text{S}}) + (1-\alpha) H(P^{\tau}_{\text{T}^{\text{full}}}, P^{\tau}_{\text{S}}), \tag{1}$$

where H refers to the cross-entropy, α is the trade-off parameter, τ is the temperature. Conducting KD with an intermediate teacher model T^{inter}, means using T^{inter} instead of T^{full} in Eq. (1).

In the standard ensemble KD setting, there are $M (M \geq 2)$ full teachers $\left\{T_1^{\text{full}}, T_2^{\text{full}}, ..., T_M^{\text{full}}\right\}$, which have the same network structure and training strategy but different initial parameters. The student

model needs to mimic the average softened softmax output of all teacher models. We call this method Full Ensemble KD. The loss function is as follows:

$$L_{\text{EKD}} = \alpha H(Y_{\text{true}}, P_{\text{S}}) + (1-\alpha) H(\frac{1}{M}\sum_{i=1}^{M} P^{\tau}_{\text{T}_i^{\text{full}}}, P^{\tau}_{\text{S}}). \tag{2}$$

The Snapshot Ensemble aggregates $M (M \geq 2)$ intermediate teachers $\{T_1^{\text{inter}}, T_2^{\text{inter}}, ..., T_M^{\text{inter}}\}$ from one training trajectory. Conducting KD with a Snapshot Ensemble, means using T_i^{inter} instead of T_i^{full} in Eq. (2). We call it Snapshot Ensemble KD.

3.2 Experimental design and setups

To examine the common assumption *"high performing teachers lead to better student models"* and explore the value of intermediate models, we design two experiments. 1) The standard KD is to train a full teacher model to distill a student model. What if we adopt the intermediate teacher models instead? 2) The standard ensemble KD is to train multiple full teacher models independently and average their output to distill a single student model. What if we adopt the Snapshot Ensemble instead of the Full Ensemble? We name the first experiment as "Intermediate Teacher vs. Full Teacher", and the second experiment as "Snapshot Ensemble vs. Full Ensemble". For generality, we conduct experiments on the CIFAR-100 [36], Tiny-ImageNet[37] and ImageNet [38] datasets with various teacher-student pairs. The distillation loss functions follow Eqs. (1) and (2). For fair comparison, we search the optimal hyperparameters (*i.e.*, the loss ratio α and the temperature τ) for each teacher-student pair. Top 1 accuracy is averagely evaluated in five independent experiments.

The "Intermediate Teacher vs. Full Teacher" experiment is conducted on the CIFAR-100 and ImageNet. On CIFAR-100, we adopt WRN-40-2[39] and ResNet-110[40] as teacher models, WRN-40-1[39], ResNet-32[40], and MobileNetV2[41] (width multiplier is 0.75) as student models. We train each teacher model for 200 epochs to ensure convergence. We save the intermediate models at the 20th, 40th, ..., 180th epochs as intermediate teachers, and the models at the 200th epoch as full teachers. On ImageNet, we adopt ResNet-50 [40], and ResNet-34 [40] as teacher models, and MobileNetV2 [41], and ResNet-18 [40] as student models. We follow the standard PyTorch practice but train teacher models for 120 epochs to guarantee convergence. We save the intermediate models at the 60th epoch as intermediate teachers, and the models at the 120th epoch as full teachers. The "Snapshot Ensemble vs. Full Ensemble" experiment is conducted on CIFAR-100 and Tiny-ImageNet. We train models for 150 epochs on Tiny-ImageNet to ensure convergence. We save the intermediate models at the 75th epoch as intermediate teachers, and the models at the 150th epoch as full teachers. We adopt WRN-40-1[39], ResNet-32[40], and MobilenetV2[41] as student models, and WRN-40-2[39], and ResNet-110[40] as teacher models. Due to the page limitation, we include the introduction of the datasets and detailed experimental settings in the Appendix A.1.

3.3 Intermediate Teacher vs. Full Teacher

Firstly, we simply compare the half-way teachers with the full teachers on CIFAR-100 and ImageNet. It means that the intermediate models at the 100th epoch are adopted as T^{inter} on CIFAR-100, the intermediate models at the 60th epoch are adopted as T^{inter} on ImageNet. The training cost of all intermediate teachers is only half that of the full teachers. Table 4 shows the comparison results. Specifically, on CIFAR-100, for WRN-40-2, the accuracy of the intermediate model is 13.54% lower than that of the full model, but its distillation performance is comparable (0.08% higher) and superior (0.96% higher). For ResNet-110, the accuracy of the intermediate model is 13.98% lower than that of the full model, but its distillation performance is still comparable (0.01% higher and 0.16% higher). On ImageNet, the accuracy of the inter-

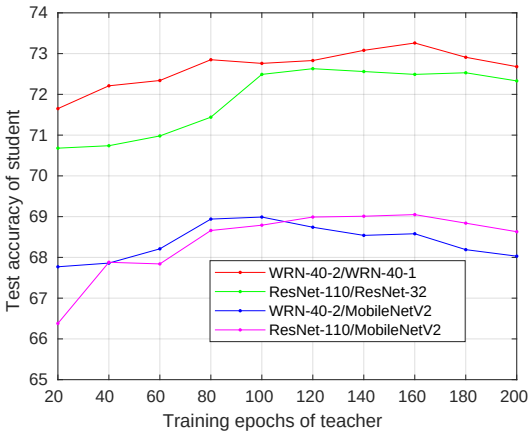

Figure 2: Ablation experiments of the training epochs of T^{inter} on CIFAR-100.

Table 1: Comparison results of "Full Teacher vs. Intermediate Teacher". T^{full} represents a full teacher. T^{inter} represents a half-way intermediate teacher whose KD performance is <u>underlined</u>. T_*^{inter} represents the best intermediate teacher whose KD performance is **bold-faced**. The numbers in brackets represent decreases (↓) or increases (↑) in accuracy.

Dataset	Network structure		Accuracy of reference models			Accuracy of KD		
	T	S	T^{full}	T^{inter}	S	T^{full}	T^{inter}	T_*^{inter}
CIFAR-100	WRN-40-2	WRN-40-1	76.53	62.99 (↓ 13.54)	70.38	72.68±0.10	<u>72.76±0.24 (↑ 0.08)</u>	**73.26**±0.03 (↑ **0.58**)
		MobileNetV2			64.49	68.03±0.34	<u>68.99±0.12 (↑ 0.96)</u>	**68.99**±0.12 (↑ **0.96**)
	ResNet-110	ResNet-32	73.41	59.43 (↓ 13.98)	70.16	72.48±0.22	<u>72.49±0.32 (↑ 0.01)</u>	**72.63**±0.13 (↑ **0.15**)
		MobileNetV2			64.49	68.63±0.35	<u>68.79±0.17 (↑ 0.16)</u>	**69.05**±0.27 (↑ **0.42**)
ImageNet	ResNet-34	ResNet-18	73.86	66.08 (↓ 7.78)	69.75	70.66	<u>70.86 (↑ 0.20)</u>	**70.98** (↑ **0.32**)
	ResNet-50	MobileNetV2	76.93	69.14 (↓ 7.79)	64.18	66.64	<u>66.79 (↑ 0.15)</u>	**66.92** (↑ **0.28**)

Table 2: Comparison results of "Full Ensemble vs. Snapshot Ensemble". EN_1 denotes T_1^{full}+T_2^{full}. EN_2 denotes T_1^{inter}+T_2^{full}. EN_3 denotes T_1^{inter}+T_1^{full}. The best results of ensemble KD performance are **bold-faced**, while the best results of ensemble performance are <u>underlined</u>.

Dataset	Network structure		Accuracy of baseline			Accuracy of ensemble KD			Accuracy of ensemble		
	T	S	T	S	KD	EN_1	EN_2	EN_3	EN_1	EN_2	EN_3
CIFAR-100	WRN-40-2	WRN-40-1	76.53	70.38	72.68±0.10	73.05±0.16	**73.80**±0.31	73.70±0.04	<u>79.44</u>	76.90	76.29
		MobileNetV2		64.49	68.03±0.34	68.69±0.32	69.14±0.27	**69.20**±0.31			
	ResNet-110	ResNet-32	73.41	70.16	72.48±0.22	72.88±0.14	72.91±0.17	**73.03**±0.24	<u>76.92</u>	74.28	73.23
		MobileNetV2		64.49	68.63±0.35	69.69±0.25	**70.46**±0.34	70.19±0.25			
Tiny-ImageNet	WRN-40-2	WRN-40-1	57.61	53.85	55.65	55.96	56.27	**56.37**	<u>62.81</u>	61.53	60.33
		MobileNetV2		53.75	56.53	56.67	57.05	**57.28**			
Average			79.32	74.11	76.04	66.11	66.61	**66.63**	<u>73.06</u>	70.90	69.95

mediate teachers is about 7.8% lower than that of the full teachers, but their distillation performance is still comparable or even better.

To further explore the potential of the intermediate models, we conduct ablation experiments of the training epochs of T^{inter} on CIFAR-100. Figure 2 shows some valuable information. 1) Good and bad teachers both improve the baseline of student model, which is consistent with [25]. 2) The peaks of all curves are not the last points, which means that there is always an intermediate teacher that is better than the full teacher. Table 4 (the last column) shows the KD performance of the best T^{inter}. 3) Generally, the accuracy curve of student first rises then decreases along with the teacher's training epochs. Combing Table 4 and Figure 2, we find a counterintuitive observation:

Observation 1. *The distillation performance of an intermediate teacher model can be comparable with or even better than that of the fully converged teacher model, although the accuracy and training cost of the former is significantly lower.*

3.4 Snapshot Ensemble[13] *v.s.* Full Ensemble

First, we fix the ensemble size to 2 to avoid introducing other factors. We train two full teacher models, T_1^{full} and T_2^{full}, with 200 epochs independently, and save their intermediate models, T_1^{inter} and T_2^{inter}, at the 100th epoch. For the Full Ensemble, we construct an ensemble with T_1^{full} and T_2^{full}. For the Snapshot Ensemble, we build an ensemble with one full teacher model T_1^{full} and its intermediate model T_1^{inter}. We use $T_1^{\text{full}} + T_2^{\text{full}}$ and $T_1^{\text{inter}} + T_1^{\text{full}}$ to represent the Full Ensemble and the Snapshot Ensemble, respectively. To further explore the intermediate and full models, we add an additional evaluation object, an ensemble with one intermediate model T_1^{inter} and one extra full teacher model T_2^{full} from another training trajectory. Such combination is represented as $T_1^{\text{inter}} + T_2^{\text{full}}$.

Table 2 shows two observations: 1) For the ensemble performance, $T_1^{\text{full}} + T_2^{\text{full}} > T_1^{\text{inter}} + T_2^{\text{full}} > T_1^{\text{full}} + T_1^{\text{inter}}$ is consistently true; 2) For the distillation performance, $T_1^{\text{inter}} + T_1^{\text{full}}$ and $T_1^{\text{inter}} + T_2^{\text{full}}$

have similar performance, but significantly outperform $T_1^{\text{full}} + T_2^{\text{full}}$. In average, the accuracy of Full Ensembles is 3.11% higher than that of Snapshot Ensembles, but the distillation accuracy of the former is 0.52% lower the latter. Comprehensively considering training cost and distillation performance, the Snapshot Ensemble ($T_1^{\text{full}} + T_1^{\text{inter}}$) is the best choice.

To further verify this cognition, we conduct an ablation experiment of the ensemble size k on CIFAR-100. We adopt WRN-40-2/WRN-40-1 as the teacher-student pair. The Full Ensemble is composed of k full teacher models, while the Snapshot Ensemble is composed of 1 full teacher model and its $k-1$ intermediate models. For simplicity, the training process of a full teacher model is averagely divided into k phases to obtain the $k-1$ intermediate models. We evaluate the test accuracy of distilled students and the total training cost, which consists of training teachers and distilling the student. Figure 3 shows two phenomena. 1) The distillation performance of the Snapshot Ensemble is significantly better than that of the Full Ensemble, with the same ensemble size k. 2) The training cost of the Snapshot Ensemble is significantly lower than that of the Full Ensemble, with the same ensemble size k. Hence, Snapshot Ensembles can be more economical and efficient in the KD setting. Combining Table 2 and Figure 3, we obtain the second counterintuitive conclusion:

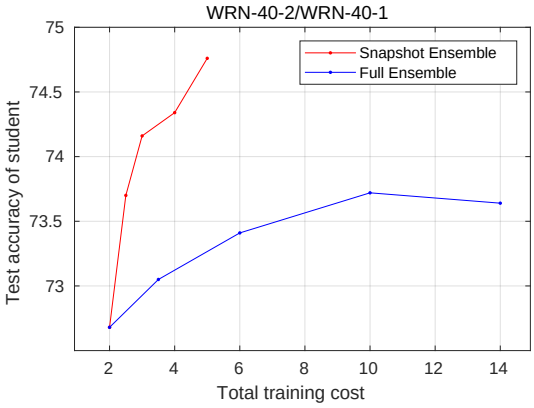

Figure 3: An ablation experiment of ensemble size ($k = 1, 2, 4, 7, 10$) on CIFAR-100. We estimate the training hours on TITAN Xp.

Observation 2. *A stronger ensemble does not always lead to a better distillation. In particular, the Snapshot Ensemble has worse ensemble performance and lower training cost but better distillation performance than the Full Ensemble.*

4 Knowledge Distillation and Information Bottleneck

We have observed that the student's accuracy first increases and then decreases while the teacher's accuracy increases monotonically, as a function of the training epoch of the teacher (as shown in Figure 2). In this section, we aim to understand this phenomenon using the IB principle proposed in [14]. The effect of mutual information on distillation performance is analyzed theoretically and experimentally, and further verified with class correlation information.

4.1 Connection knowledge distillation with information bottleneck

Tishby and Zaslavsky [14] proposed that layered neural networks form a Markov chain of successive representations of the input, and explained the optimization goal of DNNs with the IB principle. They claimed that DNNs tend to obtain an efficient representation of the input, capturing the features relevant to the output and compressing those irrelevant. Formally, for a DNN, define the input variable X and desired output variable Y. Any representation of the input F, is defined through an encoder $P(F|X)$, and a decoder $P(Y|F)$. The optimization goal of the network can be described as the following IB trade-off optimization problem [29]:

$$\min_{F} \left\{ I(X;F) - \beta I(F;Y) \right\}, \tag{3}$$

where $I(X;F)$ represents the mutual information between X and F, $I(F;Y)$ represents the mutual information between F and Y, β is a positive trade-off parameter. From a perspective of information theory, knowledge transfer can be expressed as retaining high mutual information between the teacher and student networks (proposed in VID [42]). Following Eq. (3), we define the representation of the teacher model F_t, the representation of the student model F_s. The optimization goal of the student model in KD setting can be described as follows:

$$\min_{s} \left\{ I(X;F_s) - \beta I(Y;F_s) - \gamma I(F_t;F_s) \right\}, \tag{4}$$

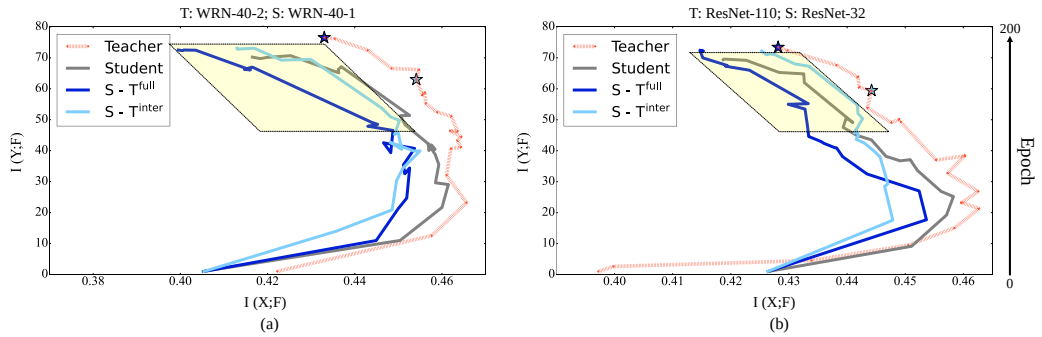

Figure 4: The mutual information curves on the information plane. The red lines represent teacher models. The dark blue ⋆ represents T^{full} while the light blue ⋆ represents T^{inter}. The gray, dark blue and light blue lines represent students, distilled students with T^{full} and distilled students with T^{inter}. The yellow areas are the observation areas. A full teacher compresses $I(X;F)$ of student, while an intermediate teacher slows down the compression (a) or even amplifies $I(X;F)$ of student (b).

where γ is a positive trade-off parameter. $I(F_t;F_s)$ represents the mutual information between the teacher and the student. F_t and F_s can be quantified by their coordinates: $(I(X;F_t), I(Y;F_t))$ and $(I(X;F_s), I(Y;F_s))$ on the information plane. Hence, maximizing $I(F_t;F_s)$ can evolve into minimizing $|I(X;F_t) - I(X;F_s)| + |I(Y;F_t) - I(Y;F_s)|$. Then, we can reformulate Eq. (4) to

$$\begin{aligned}\min_s \{ & I(X;F_s) - \beta I(Y;F_s) + \gamma |I(X;F_t) - I(X;F_s)| \\ & + \gamma |I(Y;F_t) - I(Y;F_s)| \},\end{aligned} \tag{5}$$

where how to remove the absolute value signs depends on the relative location of the coordinates $(I(X;F_t), I(Y;F_t))$ and $(I(X;F_s), I(Y;F_s))$ on the mutual information plane.

4.2 Mutual Information Analysis

In order to explore the role of mutual information in knowledge distillation, we quantitatively analyze the mutual information curves of different teacher-student pairs. In practice, following [43], we adopt the test accuracy to quantify $I(Y;F)$ and a reconstruction loss to quantify $I(X;F)$. To get the reconstruction loss, we connect a decoder following the last convolution layer of the network model to reconstruct the input X. We adopt WRN-40-2/WRN-40-1 and ResNet110/ResNet32 pairs on CIFAR-100. We train each teacher model for 200 epochs to get a full model T^{full} and save the intermediate model T^{inter} at the 100th epoch. Detailed settings are given in Appendix B.1. The mutual information curves of teacher model, student model, distilled student models with T^{full} and T^{inter} are shown in Figure 4. Some important observations and inferences are summarized.

1) The trend of all curves is similar to that shown in [29] and consistent with IB principle [14]. That is, $I(X;F)$ first goes up and then goes down while $I(Y;F)$ goes up monotonically. It can be interpreted as: for $I(X;F)$, networks first absorb information of the input X and later eliminate part of the information irrelevant to the target output Y; for $I(Y;F)$, networks continuously accumulate information relevant to the target output Y.

2) The curve of a large teacher model is usually on the right of the curve of a small student model. It means a large model generally has greater ability of information representation.

3) The full model T^{full} compresses more $I(X;F)$ but retains more $I(Y;F)$ than the intermediate model T^{inter}. That is to say, a full model may discard more information of non-target classes from X.

4) The student models distilled with T^{full} further compress $I(X;F)$ (the dark blue curves are on the left of the gray curves in Figure 4), while those distilled with T^{inter} slow down the compression of $I(X;F)$ (the light blue curve in Figure 4(a)) or even amplify $I(X;F)$ (the light blue curve in Figure 4 (b)). Retaining more $I(X;F)$ seems to be a key factor to get a competitive performance from T^{inter}.

For a full teacher with a large $I(Y;F_t)$ but a small $I(X;F_t)$, Eq. (5) is reformulated to

$$\min_s \{(1+\gamma) I(X;F_s) - (\beta+\gamma) I(Y;F_s)\}. \tag{6}$$

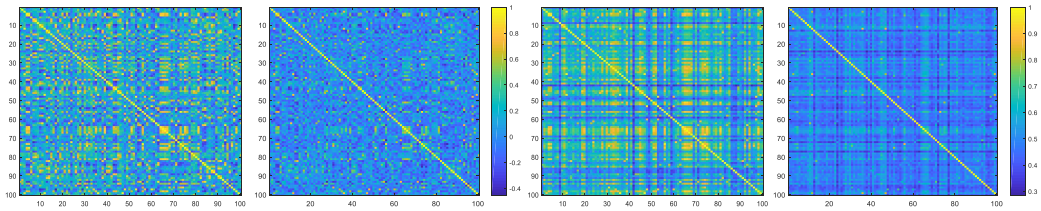

Figure 5: The heatmaps of class correlation information on the intermediate model (at the 100th epoch) and the full model (at the 200th epoch) on the CIFAR-100 dataset. (a) and (b) are calculated with the logits output; (c) and (d) are calculated with the softened softmax output (temperature is 5). More brightly colored areas mean that the intermediate model has more diversity than the full model.

For a suitable intermediate teacher model with a large $I(Y;F_t)$ and a large $I(X;F_t)$, Eq. (5) is reformulated to

$$\min_s \left\{(1-\gamma)I(X;F_s) - (\beta+\gamma)I(Y;F_s)\right\}. \tag{7}$$

Comparing Eq. (6) and Eq. (7), the difference is that a full teacher model accelerates the compression of $I(X;F_s)$ while the intermediate model alleviates the compression of $I(X;F_s)$. This is consistent with our 4th observation. Therefore, we can reasonably assume that: *more mutual information with the input data can be the main reason why an intermediate teacher model achieves better distillation performance than a full teacher model.*

Compared with a full model, a suitable intermediate model has more $I(X;F)$ and less $I(Y;F)$, which means that the intermediate model has more non-target classes information. To do further analysis, we use heatmaps of cosine similarity to visualize the class correlation information contained in the intermediate model and the full model. For CIFAR-100, a heatmap is a 100×100 matrix A, where each element A_{ij} represents the similarity between corresponding two classes. Specifically, we represent a class c_i by its average logits or softmax output on the test set (a 100-dimensional vector V_{c_i}) and then calculate the cosine similarity A_{ij} between c_i and c_j with the following equation:

$$A_{ij} = \frac{\langle V_{c_i}, V_{c_j} \rangle}{\|V_{c_i}\| \|V_{c_j}\|}. \tag{8}$$

Figure 5 shows some heatmaps of cosine similarity on the intermediate model and the full model. The network structure is WRN-40-2. Comparing Figure 5(a) with (b), we can see that the logits output of the intermediate model has better diversity than that of the full model. Comparing Figure 5(c) with (d), while using a softened softmax output with a higher temperature can increase some of the diversity between classes, the intermediate model still shows a wider range of class correlation information than the full model. Results of the class correlation information further support that a suitable intermediate teacher has more non-target classes information than a full teacher, which is consistent with the mutual information analysis.

4.3 Label smoothing regularization and knowledge distillation

The previous work [25] proposed that label smoothing regularization (LSR) can be considered as an ad-hoc KD with a pre-defined uniform distribution teacher. Mathematically for LSR, a uniform distribution u is used in place of $P^{\tau}_{\text{T}^{\text{full}}}$ in Eq. 1. We attempt to explore the connection between LSR and KD from the IB perspective. Obviously, the uniform distribution u has a small $I(Y;F_t)$ and a small $I(X;F_t)$. Eq. (5) is reformulated to

$$\underset{s}{min} \left\{(1+\gamma)I(X;F_s) - (\beta-\gamma)I(Y;F_s)\right\}, \tag{9}$$

where $\beta - \gamma$ must be positive to keep the optimization direction correct. Comparing Eq. (6) and Eq. (9), if we fix the coefficient of the second term $I(Y;F_s)$ to be 1, then the coefficient of the first term is $(1+\gamma)/(\beta+\gamma)$ in Eq. (6) and $(1+\gamma)/(\beta-\gamma)$ in Eq. (9). It means that LSR accelerates the compression of $I(X;F_s)$. In order to verify it visually, keeping the same setting as Figure 4, we add LSR to the student model and show its mutual information curve on the information plane. As shown in Figure 6, both the dark blue curve (the normal KD) and the yellow curve (LSR) are on the left of the gray curve (the student model). It means that both the normal KD and LSR play a similar role to

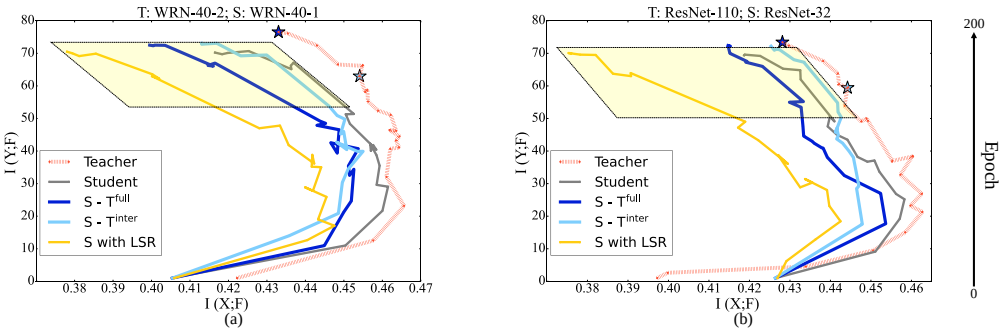

Figure 6: The mutual information curves on the information plane. The red curves represent the teacher model. The gray, dark blue and light blue curves represent the students, distilled students with full teacher and distilled students with intermediate teacher. The yellow curves represent student training with LSR. The yellow areas are the observation areas.

compress the student model's mutual information with respect to input, which supports the view in [25]. However, there is a big gap between the dark blue curve and the yellow curve, which means that the normal KD transfers more relevant information with input to the student model than the LSR does. For the distillation performance, $T^{\text{inter}} > T^{\text{full}} > u$ is consistent with the amount of $I(X; F_t)$ of the teacher models, which further supports our view in Sec. 4.2.

5 Optimal Intermediate Model Selection

As shown in Figure 2 and Figure 4, how to capture the optimal intermediate model is a non-trivial problem. An empirical conclusion is that a good intermediate model needs delicate trade-off between $I(X; F)$ and $I(Y; F)$. From the point of information entropy, the representation F of model consists of information concerning the input X, the output Y and nuisance Z which is irrelevant to the task [15]. A formal description of the entropy of F is:

$$H(F) = I(X; F) + I(Y; F) + Z. \tag{10}$$

To reduce the nuisance Z and get a more informative intermediate teacher model, we solve the following optimization problem:

$$\max_{F} \{I(X; F) + I(Y; F)\}, \tag{11}$$

where F belongs to the set of representations in intermediate teacher models. Figure 7 is an example of the selecting process. The optimal solution is usually located in the upper right corner of the information plane. Based on the selecting strategy, we propose an algorithm to find the optimal intermediate teacher for effective distillation as shown in Algorithm 1. Note that the value of mutual information $I(X; F)$ and $I(Y; F)$ is normalized to ensure the scale matching. Obtaining the optimal intermediate teacher model, standard KD or other mainstream KD methods can be conducted as usual.

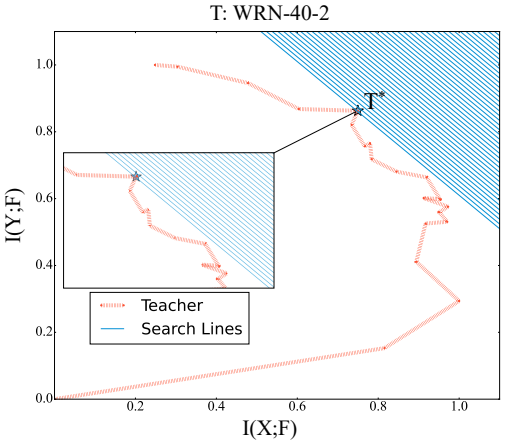

Figure 7: An example of selecting the optimal intermediate teacher T^{inter}. The red line represents the normalized mutual information curve of the teacher model (WRN-40-2) . The blue lines represent the selecting process.The star $\star$ represents the optimal intermediate teacher T^* whose representation maximizes $\{I(X; F) + I(Y; F)\}$.

To verify the superiority of the optimal intermediate model selection strategy, we conduct comparison experiments on the CIFAR-100 dataset. We keep the same experimental settings as in Sec. 3.3, but save teacher's checkpoints every 10 epochs. For each checkpoint, the information theoretic quantities $I(X; F)$ and $I(Y; F)$ are estimated as in Sec. 4.2. Then, we normalize $I(X; F)$ and $I(Y; F)$, and draw the mutual information curves. By algorithm 1, the optimal intermediate teacher models T^* of WRN-40-2 and ResNet-110 are selected at the 160th and 120th epochs respectively. An

Algorithm 1 Distillation with the optimal intermediate teacher.

1: Train a teacher model T from scratch and save its checkpoint T_i every M epochs;
2: Calculating the normalized $I(X;F)$ and $I(Y;F)$ of each T_i;
3: Draw the mutual information curve of T;
4: Find the optimal T^* which has the representation that maximizes $\{I(X;F) + I(Y;F)\}$;
5: Take T^* as the teacher model to do distillation.

Table 3: KD Results of the optimal intermediate models on CIFAR-100. The intermediate teacher models are selected at different epochs. The best results are **bold-faced**.

Network structure		Accuracy of T&S		KD accuracy of different intermediate teachers				
T	S	T	S	$T^{0.3}$	$T^{0.5}$	$T^{0.7}$	T^{full}	T^*
WRN-40-2	WRN-40-1	76.53	70.38	72.34±0.10	72.76±0.24	73.08±0.05	72.68±0.10	**73.26**±0.03
	MobileNetV2		64.49	68.21±0.33	**68.99**±0.12	68.54±0.07	68.03±0.34	68.58±0.34
ResNet-110	ResNet-32	73.41	70.16	70.74±0.18	72.49±0.32	72.46±0.30	72.48±0.22	**72.63**±0.13
	MobileNetV2		64.49	67.84±0.26	68.79±0.17	**69.01**±0.20	68.63±0.35	68.99±0.33
Average		74.97	67.38	69.78	70.76	70.77	70.46	**70.87**

empirical conclusion is that the optimal intermediate model for each teacher model may be different. To evaluate the distillation performance of T^*, we pick out models at the 60th, 100th, 140th, 200th epoch, which are denoted by $T^{0.3}$, $T^{0.5}$, $T^{0.7}$ and T^{full} as baselines. We adopt the same standard KD method [2] but different intermediate models as teachers. Table 3 shows that T^* has the best average performance, which validates the effectiveness and adaptability of our selection strategy. In addition, $T^{0.7}$ and $T^{0.5}$ also have better average performance than T^{full}. If you think that selecting the optimal intermediate model is tedious, the half-way checkpoint may be your prefer.

6 Conclusion and Limitations

In this paper, we made an observation that an intermediate model can have richer "dark knowledge" than a fully converged model, and employed the IB principle to partially interpret this phenomenon. We argue that over-training of the teacher model results in the suppression of class correlation information, leading to degradation of the distillation performance. As a result, training a fully converged teacher may not be the optimal choice, especially under resource-limited circumstances. To save training cost, we empirically suggest that the half-way teacher model can suffice. To achieve better distillation, we further proposed an optimal intermediate model selection algorithm to find the appropriate intermediate teacher. Furthermore, this work implies a more economical and efficient way to construct a snapshot ensemble with several intermediate models from the same training trajectory instead of the standard ensemble with independently full-trained models. This technique can significantly improve the ensemble model's distillation performance and reduce the training cost.

Our study also has some limitations. First, the selection of an optimal intermediate model considers the information entropy of the teacher but ignore the variation of the student structures, which can not ensure the optimal KD performance for all teacher-student pairs. Second, how to choose the best intermediate teacher model for a specific structure of student is still a challenging problem.

Acknowledgement

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References

[1] Cristian Bucila, Rich Caruana, and Alexandru Niculescu-Mizil. Model compression. In *KDD '06*, 2006.

[2] Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean. Distilling the knowledge in a neural network. *CoRR*, abs/1503.02531, 2015.

[3] Tommaso Furlanello, Zachary Chase Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar. Born-again neural networks. In *ICML*, 2018.

[4] Ying Zhang, Tao Xiang, Timothy M. Hospedales, and Huchuan Lu. Deep mutual learning. In *CVPR*, 2018.

[5] Shan You, Chang Xu, Chao Xu, and Dacheng Tao. Learning from multiple teacher networks. In *KDD*, 2017.

[6] Defang Chen, Jian-Ping Mei, Can Wang, Yan Feng, and Chun Chen. Online knowledge distillation with diverse peers. In *AAAI*, 2020.

[7] Zheng Li, Ying Huang, Defang Chen, Tianren Luo, Ning Cai, and Zhigeng Pan. Online knowledge distillation via multi-branch diversity enhancement. In *ACCV (4)*, 2020.

[8] Seyed-Iman Mirzadeh, Mehrdad Farajtabar, Ang Li, Nir Levine, Akihiro Matsukawa, and Hassan Ghasemzadeh. Improved knowledge distillation via teacher assistant. In *AAAI*, 2020.

[9] Mengya Gao, Yujun Shen, Quanquan Li, and Chen Change Loy. Residual knowledge distillation. *CoRR*, abs/2002.09168, 2020.

[10] Chenglin Yang, Lingxi Xie, Siyuan Qiao, and Alan L Yuille. Training deep neural networks in generations: A more tolerant teacher educates better students. In *AAAI*, volume 33, pages 5628–5635, 2019.

[11] Dae Young Park, Moon-Hyun Cha, Daesin Kim, Bohyung Han, et al. Learning student-friendly teacher networks for knowledge distillation. *NeurIPS*, 34, 2021.

[12] Jang Hyun Cho and Bharath Hariharan. On the efficacy of knowledge distillation. In *ICCV*, pages 4794–4802, 2019.

[13] Gao Huang, Yixuan Li, Geoff Pleiss, Zhuang Liu, John E. Hopcroft, and Kilian Q. Weinberger. Snapshot ensembles: Train 1, get M for free. In *ICLR (Poster)*, 2017.

[14] Naftali Tishby and Noga Zaslavsky. Deep learning and the information bottleneck principle. In *ITW*, 2015.

[15] Alessandro Achille and Stefano Soatto. Emergence of invariance and disentanglement in deep representations. In *ITA*, 2018.

[16] Jianping Gou, Baosheng Yu, Stephen J Maybank, and Dacheng Tao. Knowledge distillation: A survey. *International Journal of Computer Vision*, 129(6):1789–1819, 2021.

[17] Adriana Romero, Nicolas Ballas, Samira Ebrahimi Kahou, Antoine Chassang, Carlo Gatta, and Yoshua Bengio. Fitnets: Hints for thin deep nets. In *ICLR (Poster)*, 2015.

[18] Sergey Zagoruyko and Nikos Komodakis. Paying more attention to attention: Improving the performance of convolutional neural networks via attention transfer. In *ICLR (Poster)*, 2017.

[19] Chaofei Wang, Jiayu Xiao, Yizeng Han, Qisen Yang, Shiji Song, and Gao Huang. Towards learning spatially discriminative feature representations. In *ICCV*, pages 1326–1335, 2021.

[20] Junho Yim, Donggyu Joo, Ji-Hoon Bae, and Junmo Kim. A gift from knowledge distillation: Fast optimization, network minimization and transfer learning. In *CVPR*, 2017.

[21] Frederick Tung and Greg Mori. Similarity-preserving knowledge distillation. In *ICCV*, 2019.

[22] Baoyun Peng, Xiao Jin, Dongsheng Li, Shunfeng Zhou, Yichao Wu, Jiaheng Liu, Zhaoning Zhang, and Yu Liu. Correlation congruence for knowledge distillation. In *ICCV*, 2019.

[23] Chaofei Wang, Ke Yang, Shaowei Zhang, Gao Huang, and Shiji Song. Tc3kd: Knowledge distillation via teacher-student cooperative curriculum customization. *Neurocomputing*, 508:284–292, 2022.

[24] Xu Lan, Xiatian Zhu, and Shaogang Gong. Knowledge distillation by on-the-fly native ensemble. In *NeurIPS*, 2018.

[25] Li Yuan, Francis E. H. Tay, Guilin Li, Tao Wang, and Jiashi Feng. Revisit knowledge distillation: a teacher-free framework. *CoRR*, abs/1909.11723, 2019.

[26] Linfeng Zhang, Jiebo Song, Anni Gao, Jingwei Chen, Chenglong Bao, and Kaisheng Ma. Be your own teacher: Improve the performance of convolutional neural networks via self distillation. In *ICCV*, pages 3713–3722, 2019.

[27] Chenglin Yang, Lingxi Xie, Chi Su, and Alan L Yuille. Snapshot distillation: Teacher-student optimization in one generation. In *CVPR*, pages 2859–2868, 2019.

[28] Naftali Tishby, Fernando C. N. Pereira, and William Bialek. The information bottleneck method. *CoRR*, physics/0004057, 2000.

[29] Ravid Shwartz-Ziv and Naftali Tishby. Opening the black box of deep neural networks via information. *CoRR*, abs/1703.00810, 2017.

[30] Ziv Goldfeld, Ewout van den Berg, Kristjan H. Greenewald, Igor Melnyk, Nam Nguyen, Brian Kingsbury, and Yury Polyanskiy. Estimating information flow in deep neural networks. In *ICML*, 2019.

[31] Andrew M. Saxe, Yamini Bansal, Joel Dapello, Madhu Advani, Artemy Kolchinsky, Brendan D. Tracey, and David D. Cox. On the information bottleneck theory of deep learning. In *ICLR (Poster)*, 2018.

[32] Roman Pogodin and Peter E. Latham. Kernelized information bottleneck leads to biologically plausible 3-factor hebbian learning in deep networks. In *NeurIPS*, 2020.

[33] Anirudh Goyal, Riashat Islam, Daniel Strouse, Zafarali Ahmed, Hugo Larochelle, Matthew Botvinick, Yoshua Bengio, and Sergey Levine. Infobot: Transfer and exploration via the information bottleneck. In *ICLR (Poster)*, 2019.

[34] Xingyu Lu, Kimin Lee, Pieter Abbeel, and Stas Tiomkin. Dynamics generalization via information bottleneck in deep reinforcement learning. *CoRR*, abs/2008.00614, 2020.

[35] Jiameng Fan and Wenchao Li. Robust deep reinforcement learning via multi-view information bottleneck. *CoRR*, abs/2102.13268, 2021.

[36] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. *University of Toronto*, 2009.

[37] Tiny-imagenet. `https://tiny-imagenet.herokuapp.com/`.

[38] 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.

[39] Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. In *BMVC*, 2016.

[40] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

[41] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *CoRR*, abs/1704.04861, 2017.

[42] Sungsoo Ahn, Shell Xu Hu, Andreas Damianou, Neil D Lawrence, and Zhenwen Dai. Variational information distillation for knowledge transfer. In *CVPR*, pages 9163–9171, 2019.

[43] Yulin Wang, Zanlin Ni, Shiji Song, Le Yang, and Gao Huang. Revisiting locally supervised learning: an alternative to end-to-end training. In *ICLR*, 2021.

[44] Min Lin, Qiang Chen, and Shuicheng Yan. Network in network. In *ICLR (Poster)*, 2014.

[45] Ilya Loshchilov and Frank Hutter. SGDR: stochastic gradient descent with warm restarts. In *ICLR (Poster)*, 2017.

[46] Y. Wang, Z. Ni, S. Song, L. Yang, and G. Huang. Revisiting locally supervised learning: an alternative to end-to-end training. 2021.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 6.
   (c) Did you discuss any potential negative societal impacts of your work? [No] We could not foresee any potential negative societal impacts of our work.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] See Section 4.
   (b) Did you include complete proofs of all theoretical results? [Yes] See Section 4.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We provide the URL of code for reproducing the main results.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 3.2,Section 4.2,Section 5 and the Appendix.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] In the paper, top 1 accuracy is averagely evaluated in five independent experiments.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Figure 3 and Figure 9.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See Section 3.2.
   (b) Did you mention the license of the assets? [No] The models and the datasets are open source.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We provide the URL of code for reproducing the main results.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No] We only use open source datasets.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] We only use open source datasets.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Exploratory experiments

A.1 Datasets and experimental settings

The "Intermediate Teacher vs. Full Teacher" experiment is conducted on the CIFAR-100 [36] and ImageNet [38] datasets. The CIFAR-100 contains 50,000 training images with 500 images per class and 10,000 test images with 100 images per class, and comprises 32×32 pixel RGB images with 100 classes. The ImageNet dateset contains 1.2 million images for training and 50,000 for validation from 1,000 classes.

On CIFAR-100, we use a standard data augmentation scheme [44], in which the images are zero-padded with 4 pixels on each side, randomly cropped to produce 32×32 images, and horizontally mirrored with probability 0.5. WRN-40-2 [39] and ResNet-110 [40] are adopted as teacher models, while WRN-40-1 [39], ResNet-32 [40], and MobileNetV2 [41] are adopted as student models. In this paper, we use MobileNetV2 with its width multiplier set to 0.75. We train each teacher model for 200 epochs with batch size 128, cosine learning rate schedule [45] gradually decaying from 0.1 to 0, weight decay 5e-4, and SGD optimizer with momentum 0.9. We save the intermediate models at the 20th, 40th, ..., 180th epoch as "Intermediate Teachers", and the final models at the 200th epoch as "Full Teachers".

On ImageNet, we adopt MobileNetV2 [41], ResNet-18 [40] as student models and ResNet-50 [40], ResNet-34 [40] as teacher models. We follow the standard PyTorch practice but train teacher models for 120 epochs. The 120th checkpoints are taken as the full teachers while the 60th checkpoints are adopted as the intermediate teachers.

We distill the student models by the same way as [2] except for the hyperparameters. To perfectly show the performance of each network, we search for the optimal hyperparameters (*i.e.*, the loss ratio α and the temperature τ) to each teacher-student pair as shown in Table 4. Generally, intermediate models at the later training stages tend to choose a larger τ and a smaller α.

The "Snapshot Ensemble vs. Full Ensemble" experiment is conducted on CIFAR-100 [36] and Tiny-ImageNet [37]. Tiny-ImageNet consists of a subset of ImageNet dataset. There are 100,000 images for training and 10,000 images for validation from 200 classes. All images are 64×64 colored ones. Some different settings on Tiny-ImageNet include: 1) we train models for 150 epochs on Tiny-ImageNet while 200 epochs on CIFAR datasets; 2) we add a stride of 2 to the first layer of the CIFAR models, in order to downsample the images to the same 32×32 resolution, following [13]. For fair comparison, we also use grid search to find the best value of hyperparameters τ and α, as shown in Table 5.

A.2 More visual comparison results

Figure 3 only shows the results of total computational cost (teacher and student together) vs. distillation performance between Snapshot Ensemble and Full Ensemble. To show it more comprehensively, we add to show the results of total computational cost vs. distillation performance for five teacher models (T^{inter}, T^{full}, T^{*}, $T_1^{\text{inter}} + T_1^{\text{full}}$, $T_1^{\text{full}} + T_2^{\text{full}}$) on four teacher-student pairs. As shown in Figure 8, the curve of T^{inter} is on the upper left of that of T^{full}, and the curve of $T_1^{\text{inter}} + T_1^{\text{full}}$ is on the upper left of that of $T_1^{\text{full}} + T_2^{\text{full}}$. In Figure 8, "upper left" means lower computational cost but higher distillation performance. T^{*} has higher distillation performance than T_1^{full} and T_1^{inter}, but T^{*} needs higher computational cost (though lower than $T_1^{\text{full}} + T_2^{\text{full}}$). The current optimal intermediate model selection algorithm needs additional computational cost, which means that there is plenty of room for improvement. A practical suggestion is: in the case of limited computing resources, the half-way teacher model (*i.e.*, $T^{0.5}$) can suffice for KD. In the case of sufficient computing resources, the optimal intermediate model selection algorithm can be used to find an appropriate checkpoint to achieve better performance.

A.3 Effects of early stopping

In the paper, we training teacher models for a fixed number of epochs, such as 200 epochs on CIFAR, 120 epochs on ImageNet. In practice, the early stopping strategy is often used to avoid model overfitting. To investigate the possible effects of early stopping, we adopt the general early stopping strategy (patience=10) in the training process. We show the training curves of all teacher models

Table 4: Optimal hyperparameters (temperature τ and ratio α) for all used intermediate and full teachers on CIFAR-100 and ImageNet.

Dataset	T	WRN-40-2		ResNet-110	
	S	WRN-40-1	MobileNetV2	ResNet-32	MobileNetV2
CIFAR-100	T^{20}	τ=5, α=0.7	τ=5, α=0.7	τ=5, α=0.9	τ=5, α=0.7
	T^{40}	τ=5, α=0.7	τ=5, α=0.7	τ=5, α=0.9	τ=5, α=0.7
	T^{60}	τ=5, α=0.7	τ=5, α=0.7	τ=5, α=0.9	τ=7, α=0.5
	T^{80}	τ=5, α=0.7	τ=9, α=0.5	τ=5, α=0.9	τ=7, α=0.5
	T^{100}	τ=7, α=0.7	τ=9, α=0.5	τ=7, α=0.7	τ=7, α=0.5
	T^{120}	τ=7, α=0.7	τ=9, α=0.5	τ=7, α=0.7	τ=7, α=0.5
	T^{140}	τ=9, α=0.5	τ=9, α=0.5	τ=7, α=0.7	τ=9, α=0.3
	T^{160}	τ=9, α=0.5	τ=9, α=0.3	τ=9, α=0.7	τ=9, α=0.3
	T^{180}	τ=9, α=0.5	τ=15, α=0.1	τ=9, α=0.5	τ=9, α=0.3
	T^{200}	τ=9, α=0.5	τ=15, α=0.1	τ=9, α=0.5	τ=9, α=0.3
Dataset	T - S	ResNet-34 - ResNet-18		ResNet-50 - MobileNetV2	
ImageNet	T^{20}	τ=1.5, α=0.5		τ=1.5, α=0.7	
	T^{40}	τ=1.5, α=0.5		τ=1.5, α=0.7	
	T^{60}	τ=1.5, α=0.3		τ=1.5, α=0.5	
	T^{80}	τ=2, α=0.3		τ=1.5, α=0.5	
	T^{100}	τ=2, α=0.1		τ=2, α=0.5	

Table 5: Optimal hyperparameters (temperature τ and ratio α) for Snapshot Ensemble and Full Ensemble on CIFAR-100 and Tiny-ImageNet.

Dataset	T	WRN-40-2		ResNet-110	
	S	WRN-40-1	MobileNetV2	ResNet-32	MobileNetV2
CIFAR-100	Snapshot Ensemble	τ=5, α=0.5	τ=7, α=0.3	τ=9, α=0.5	τ=9, α=0.3
	Full Ensemble	τ=5, α=0.5	τ=20, α=0.1	τ=9, α=0.5	τ=9, α=0.3
Dataset	T - S	WRN-40-2 - WRN-40-1		WRN-40-2 - MobileNetV2	
Tiny-ImageNet	Snapshot Ensemble	τ=3, α=0.5		τ=3, α=0.5	
	Full Ensemble	τ=5, α=0.5		τ=5, α=0.5	

in Figure 9. Overall, training the teacher models on CIFAR for 200 epochs and ImageNet for 120 epochs does not lead to model overfitting. The optimal checkpoints are located on the left of the positions of early stopping. Therefore, using the early stopping strategy does not affect the results.

B Mutual information experiments

B.1 Estimation of mutual information

Mutual information is difficult to calculate accurately, especially in the case of unknown joint probability distribution or continuous random variables. In this paper, we estimate the mutual information $I(X;F)$ between input X and representation F with a reconstruction loss following

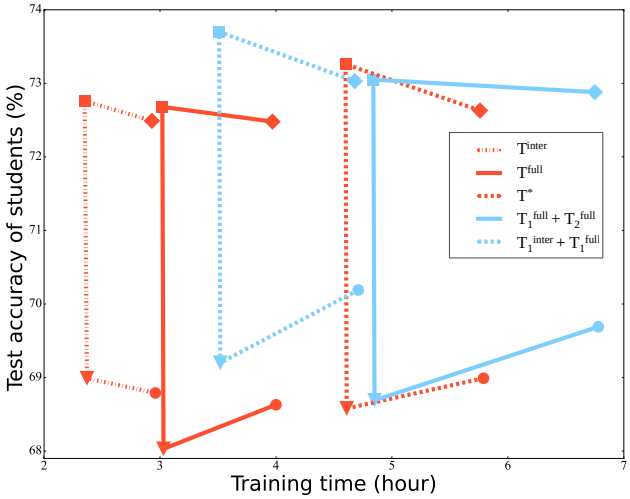
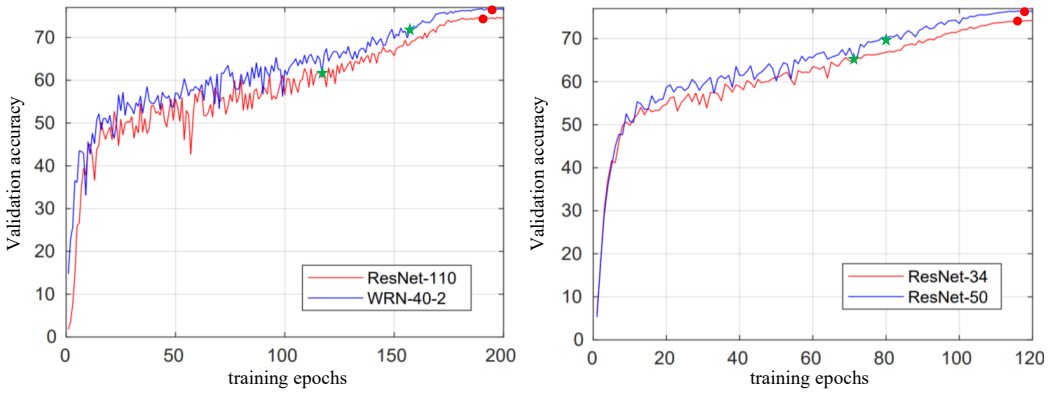


Figure 8: Computational cost vs. distillation performance for different teacher models on CIFAR-100. T^{inter} denotes a half-way teacher. T^{full} denotes a convergent teacher. $T_1^{\text{inter}} + T_1^{\text{full}}$ denotes Snapshot Ensemble teacher. $T_1^{\text{full}} + T_2^{\text{full}}$ denotes Full Ensemble teacher. T^* denotes the optimal checkpoint obtained by our search algorithm. $\square$ denotes WRN-40-2/WRN-40-1. $\triangle$ denotes WRN-40-2/MobileNetV2. $\diamond$ denotes ResNet-110/ResNet-32. $\circ$ denotes ResNet-110/MobileNetV2.



(a) Training teachers on CIFAR-100

(b) Training teachers on ImageNet

Figure 9: The training curves of all teacher models. (a) WRN-40-2 and ResNet-100 trained on CIFAR-100. (b) ResNet-50 and ResNet-34 trained on ImageNet. The red $\bullet$ denotes the position of early stopping, while the green $\star$ denotes the position of the optimal checkpoints.

[46]. Specifically, we connect a decoder to the last convolution layer of a trained and fixed network model in order to generate a pseudo input image $\overline{X}$. The structure of the decoder is shown in Table 6). Then we train the decoder to convergence with the Adam optimizer and binary cross-entropy loss between $\overline{X}$ and X. This reconstruction loss is used to estimate $I(X;F)$. For the mutual information $I(Y;F)$ between output Y and representation F, we use the trained network model to do inference on the test dataset, and estimate $I(Y;F)$ with the test accuracy.

B.2 More results of class correlation information

The results of heatmaps in Figure 5 show that the appropriate intermediate model has better diversity than the full model. To clearly display differences of class correlation information between the intermediate model and the full model, we randomly sample four classes from the test dataset and calculate the average logits output of each class. Figure 10 shows that the logits output of the

Table 6: Architecture of the decoder.

Input: 240×240 / 128×128 / 64×64 feature maps
Bilinear Interpolation to 32×32
3×3 conv., stride=1, padding=1, output channels=12, BatchNorm+ReLU
3×3 conv., stride=1, padding=1, output channels=3, Sigmoid

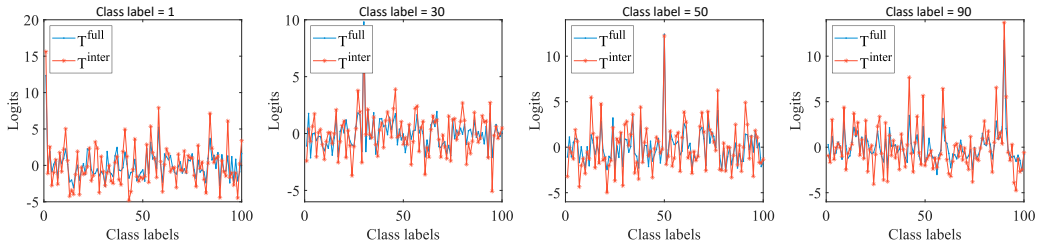


Figure 10: The average logits outputs of 4 random classes on the intermediate model (at the 100th epoch) and the full model (at the 200th epoch). The red curves have more peaks and greater variances than the blue curves, which indicates that T^{inter} has more non-target class information than T^{full}.

intermediate model has more peaks and larger variance than that of the full model. Specifically, the intermediate model reserves plentiful valuable non-target "misclassifications", which are mostly eliminated in the full model. Such non-target information implicitly illustrates certain correlation among classes thus significantly complements the rigid one-hot label.