How to Teach: Learning Data-Free Knowledge Distillation from Curriculum

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Abstract—Data-free knowledge distillation (DFKD) aims at training lightweight student networks from teacher networks without training data. Existing approaches mainly follow the paradigm of generating informative samples and progressively updating student models by targeting data priors, boundary samples or memory samples. However, it is difficult for the previous DFKD methods to dynamically adjust the generation strategy at different training stages, which in turn makes it difficult to achieve efficient and stable training. In this paper, we explore how to teach students the model from a curriculum learning (CL) perspective and propose a new approach, namely "CuDFKD", i.e., "Data-Free Knowledge Distillation with Curriculum". It gradually learns from easy samples to difficult samples, which is similar to the way humans learn. In addition, we provide a theoretical analysis of the majorization minimization (MM) algorithm and explain the convergence of CuDFKD. Experiments conducted on benchmark datasets show that with a simple course design strategy, CuDFKD achieves the best performance over state-of-the-art DFKD methods and different benchmarks, such as 95.28% top1 accuracy of the ResNet18 model on CIFAR10, which is better than training from scratch with data. The training is fast, reaching the highest accuracy of 90% within 30 epochs, and the variance during training is stable. Also in this paper, the applicability of CuDFKD is also analyzed and discussed.

Index Terms—Data-Free Knowledge Distillation, Curriculum Learning, Self-paced learning.

I. INTRODUCTION

Knowledge Distillation (KD) [1]–[5] provides a convenient approach for training smaller student networks by distilling knowledge from the large pretrained teacher models. The vanilla KD follows the paradigm of minimizing the divergence of output distribution on training data from the teacher model and student model.

However, in real-world scenarios, the training data for KD is usually not accessible due to privacy protection [6] or limited resources for training on large benchmarks like ImageNet [7]. Data-Free Knowledge Distillation (DFKD, or ZSKD [8]–[10]) aims at training student models without training data. When there’s no access to the original data, DFKD designs a target for the generation of pseudo samples. More specifically, by reversing inference knowledge from the teacher model, the student network is trained with progressively generated pseudosamples, which are an approximation of an unknown target distribution.

The target here is critical for DFKD because it controls the quality of generation and further controls the performance of KD. Previous DFKD methods define different types of targets, including data prior [11], [12], adversarial samples [13]–[15] or previous memory samples [16]–[18]. Although the aforementioned methods are followed by a progressive process, they do not explicitly adjust the generation target dynamically with the learning capacity of the student network, especially in the early stages of training. As the student in the early stages has limited learning ability, it’s necessary to clarify whether the generated pseudo sample can better help on the training of KD, i.e., how to effectively select and teach the knowledge at different stages of training so that the student learns better?

Intuitively, the training process of DFKD is similar to human learning, where the training samples should be arranged scientifically according to the complexity and the behavior of the student network. In human learning, for example, it’s reasonable for a teacher to teach arithmetic first and calculus later instead of teaching arithmetic and calculus at a time. The teacher should dynamically adjust the teaching strategy to the learning ability of the student. The above training process is conformed to curriculum learning (CL) [19], [20], which learns the easiest part of training data first and then harder data. It adjusts the difficulty of training data by a difficulty measurer and a training scheduler. This easy-to-hard process provides another target information to DFKD, i.e., design a generative model for KD by the guidance of the CL algorithm.

TABLE I: Comparison between CuDFKD and previous DFKD methods. Student means the target of generation takes the training process of student into consideration. Dynamic means dynamically update the generation target at different timestamps of KD.

| Method       | Target    | Student | Dynamic |
|--------------|-----------|---------|---------|
| DAFL [11]    | Data Prior| No      | No      |
| DFQ [13]     | Adversarial| Yes    | No      |
| CMI [16]     | Memory    | No      | Yes     |
| CuDFKD(Ours) | Difficulty| Yes    | Yes     |

In this paper, we explore a novel learning strategy for DFKD, which generates the pseudo samples from easy to hard in a curriculum manner and adjust the student capability. Different from previous DFKD methods, our method uses a more adaptive and flexible strategy to generate the pseudo samples by design a CL strategy. We define the difficulty for different training stages of DFKD as divergence between teacher and student model. To implement the CL strategy, we propose a simple but effective AOS algorithm for DFKD method based on curriculum learning, called CuDFKD. Theoretically, CuDFKD are promised to convergence by the theory of self-
paced learning(SPL) [21] and majorization minimization(MM) [22]. Practically, it is realized by dynamically adjust the gradient of adversarial samples and reweighting the generated pseudo samples. We compare CuDFKD with other DFKD methods by table I.

The contributions of this paper are summarized as:
- We propose a simple but effective DFKD method by dynamically adjusting the difficulty of generated pseudo samples, called CuDFKD. It’s the first method to dynamically and explicitly match the process of generating pseudo samples with the training process of the student model, and we prove that it reaches convergence by the theory of MM.
- We provide a detailed analysis and discussion of the advantages of CuDFKD over memory-based and boundary-based DFKD methods, and also explore the future improvement of CuDFKD.
- Our CuDFKD achieves the best performance of CIFAR10 with a ResNet18 validation accuracy of 95.28%, and also has comparable results to other SOTA methods. Furthermore, CuDFKD is the most stable and efficient method among all the benchmarks, even when the teacher is noisy. CuDFKD also performs well when the teacher is noisy.

This paper is organized as following: section II reviews some related works about DFKD and curriculum learning, section III discuss some basic concepts about curriculum learning and self-pace learning. Section IV discuss how to build up CuDFKD, and proves its convergence by MM theory. Section V reports some results and discussion about CuDFKD. Finally, Section VI concludes this paper and discusses the future works.

II. RELATED WORKS

In this section, we review the previous works of DFKD and curriculum learning and compare their differences with CuDFKD.

A. Data-Free Knowledge Distillation

According to the target information for the generation of pseudo samples mentioned in section I, we categorize DFKD methods into three types, as prior-based DFKD, boundary-based DFKD, and Memory-based DFKD.

The prior-based DFKD methods [8], [11], [12], [23] use inversion methods to imitate the original data distribution. ZSKD [8]–[10] and SoftTarget [23] models the output label distribution or intermediate feature maps by simple distributions. DAFL [11], DeepInversion, and Adaptive DeepInversion [12] design different regularization terms, like adversarial divergence or batch normalization statistics, for realistic and useful pseudo data samples. Moreover, some limited-data KD models use similar targets to guide the training stage, like [24].

The boundary-based DFKD methods [12]–[15], [25] are motivated by the idea of GANs [26], the generative models generate samples to maximize the gap between the output distribution of teacher and student models. [25], [27] treats the pretrained teacher model as a black-box model and uses a min-max game to update the generator and student models. DFQ [13] dynamically balances the sample generation between prior-based and boundary-based, and design instance/category entropy loss for prior regularization. Qimera [14] explores the effect of boundary samples on the model quantization, which provides a similar perspective to KD. They learn the samples near the decision boundary of the teacher model first, and they treat such samples as hard samples. Typically, such methods get robust student models and also high performance.

Some researchers discover that the training of DFKD can suffer catastrophic forgetting, i.e., some learned useful knowledge or gradients cannot preserve during training, and thus the later student is trapped into local minima. The memory-based DFKD methods are proposed to rephrase the learned knowledge from the early student model. like CMI [16], PRE-DFKD [17] and MB-DFKD [18] are motivated by continual learning [28], [29], they use memory samples to avoid the catastrophic forgetting problem during KD training, and get extraordinary performance on different benchmarks. They preserve the knowledge from the early student model by setting up a memory bank [16], [18] or reconstruction [18] process and thus help the training by the target of student model at different training targets. Compared with CuDFKD, memory-based DFKD still needs extra memory usage or parameter training, while our CuDFKD only uses a non-parameterized training scheduler and difficulty measurer.

For the application of DFKD, it also extends to the graph data as "graph-free distillation" [30], [31], and they are applicable in many tasks like regression [32], object detection [33] and image super-resolution [34].

B. Curriculum Learning(CL)

Curriculum learning [19], [20], [35] is a learning strategy that "training the models from easier data to harder data". [19] provides a clear illustration of the convergence of curriculum that CL is a particular continuation method. Therefore, according to how to design a proper curriculum, the existing CL methods are categorized into predefined CL [36]–[38] and automatic CL [21], [29], [38], [39].

Compared with predefined CL, automatic CL is more general and dynamic to the model architecture and training process, and it also avoids the potential effect of predefined expert knowledge. Thus their difficulty measurers are more flexible to the training model. The most widely used automatic CL is self-paced learning(SPL) [21], [29], which dynamically assigns data with different difficulties by the training losses at each timestamp (or epoch). [40]–[43] provide theoretical understanding of SPL, and they are categorized into majorization minimization (MM) [44] algorithm and concave optimization. ScreenerNet [45] also learns a curriculum by designing a deep neural network, which provides a connection between the deep models and CL.

Some automatic methods use a pretrained teacher model on the training dataset or an external dataset and then transfer the knowledge from the teacher to schedule the difficulty. They use transfer learning [35], [46], bootstrapping [47], noise score
Uncertainty [49] as the specific representative to transfer from teacher. They are similar to the setting of KD, but the "teacher" here is external and thus is a different domain with students.

Recently, some full-data KD tasks also use CL to help the student better learn the knowledge from the teacher. [50] uses self-paced learning for the instance selection of long-tailed datasets. [51] use a similar uncertainty curriculum to distill the model from large pretrained language models like BERT [52].

In this work, CL provides an adaptive training target for the generation process of DFKD. Besides, it also provides a theoretical understanding for accelerating the convergence of DFKD methods, and it contributes to the usage of CL.

III. PRELIMINARY ON CURRICULUM LEARNING

Curriculum Learning (CL) is widely used in full-data scheme, i.e., given a training dataset $D = \{(x, y)\}$, where $y$ is the label of specific data $x$. CL defines a difficulty scheduler $d(x, t)$ to evaluate the difficulty of data samples, and a training scheduler to find the subset $D_i$ of training data at this difficulty. CL is designed to achieve the optimal parameter $\theta^*$ by proper schedulers, and the data subset series is easy-to-hard. If the difficulty function is continuous, the subset series should satisfy $\partial d(D_i, t)/\partial t > 0$.

Instead of manually designing two schedulers, Self-Paced Learning (SPL) [21] dynamically update difficulty by the training loss $L(x, y; \Theta)$. What’s more, they define a reweighting factor $v$ as a training scheduler, and the objective is,

$$\min_{w \in \mathbb{R}^d, v \in [0, 1]^d} F(w, v) = v(\lambda, L)T L(x, y; \Theta) + g(\lambda, v)$$

Where the convex function $g(\lambda, v)$ is called Self-Paced regularizer (SP-regularizer). The optimal $v^*(\lambda, L) = \arg\min_v F(w, v)$. Here $g(\lambda, v)$ is designed under some constraints (See [20], [21]). It is either explicit [21], [29], [53], [54] or implicit [55]–[57]. There are many theoretical analyses on how to optimize equation 1. [20] concludes that optimizing equation 1 equals to optimize the following latent equation,

$$\sum_{i=1}^{N} F(\lambda, L_i) = \sum_{i=1}^{N} \int_0^{L_i} v^*(\lambda, L) dL$$

Here optimizing $\sum_{i=1}^{N} F(\lambda, L_i)$ converges to the critical points of original SPL under mild conditions [40], thus promises its convergence.

IV. DESIGN AND DISCUSSION OF CuDFKD

In this section, we implement the SPL framework to DFKD, and propose an algorithm to progressively update all the parameters. Finally, we give a discussion about why does CuDFKD work. The overall workflow of CuDFKD is presented in Fig 1.
A. Difficulty Definition

Compared with previous CL methods [19], [46], the dataset \( D \) is not available. Therefore, we consider to build a difficulty measure \( d(p_\theta(x), t) \) with respect to the built distribution estimator \( p_\theta(x) \) and timestamp \( t \), and it should satisfy the following criteria:

- The difficulty measure should monotonically non-decreasing w.r.t. timestamp \( t \), i.e., \( \frac{\partial d(p_\theta(x), t)}{\partial t} \geq 0 \).
- The difficulty measure guides the training of the generated data distribution, i.e., find a proper parameter \( \theta^* = \arg \min_\theta f(d(p_\theta(x), t), \nu^*) \), where \( f \) is a type of loss function.

Motivated by boundary-based methods [13]–[15] in DFKD, the samples are close to the decision boundary and are regarded as the hard sample. Thus we can make a tractable definition of difficulty measurer for a set of data \( D \), i.e.,

\[
d(D, t) = \mathbb{E}_{x \sim D}[D(p_\theta(x)|p_\theta(x))].
\]

Here \( D \) is some divergence function. For the generation stage, it minimizes \( F(\phi, \nu, \theta) \) to replace the objective function. Therefore, the modeled \( p_\theta(x) \) generates the samples with scheduled difficulty by adjusting the grad \( \partial d(p_\theta, t)/\partial \theta \) and the curriculum strategy \( \nu^* \) is further calculated to control the difficulty at fine-grained. Thus, the reweighting factor \( \nu^* \) is treated as another target for DFKD. Combined with the discussion of difficulty measure above, the objective function is,

\[
\min_{\phi_s, \nu \in [0, 1]^d, \theta} F(\phi_s, \nu, \theta) = \nu(\lambda, t)^T \mathbb{E}_{x \sim p_\theta}[L(f_s(x), f_s(x; \phi_s))] + g(\lambda, \nu) \tag{3}
\]

Here \( f_s() \) and \( f_s() \) represent the teacher and student model, and \( \nu^* \) is a function from data to data difficulty at timestamp \( t \). Therefore, we design an algorithm that dynamically updates \( \theta, \phi_s, \) and \( \nu \).

B. Training Procedure of CuDFKD

Combined with the difficulty definition above, we propose a new DFKD method called \textbf{CuDFKD}. However, there still exist some gaps in practically implementing CL strategy, including:

- Optimize \( \theta \) and \( \phi_s \) jointly in CuDFKD.
- Properly defines the loss function of the generative model \( L_\theta \) to gradually increase the difficulty with the training timestamps \( t \).

Therefore, we propose an alternative updating strategy for all the parameters, i.e., in each epoch we train the generator \( \theta \) and student model \( \phi_s \) alternatively. For the generation stage of updating \( \theta \), we build an objective for generating pseudo samples motivated by previous DFKD methods [12], [13], [16], i.e.,

\[
\min_\theta L_\theta = \mathbb{E}_{x \sim p_\theta(x)}[-\alpha_{adv}(t)D(f_s(x), f_s(x)) + L_\theta(x)] \tag{4}
\]

Here the divergence function \( D \) is either Jensen–Shannon(JS) divergence or Kullback–Leibler(KL) divergence. \( L_\theta(x) \) is a loss function for regularizing the pretrained teacher model and improving the quality for the generation of pseudo samples. \( L_\theta(x) \) includes categorical entropy [13], batch normalization statistics alignment [12] and activation normalization [58]. The regularization item \( L_\theta \) is designed by,

\[
L_\theta(x) = \alpha_{bn} L_{bn} + \alpha_{oh} L_{oh} = \alpha_{bn} \sum_i (D(\mu_i, \mu_{bn,i}) + D(\sigma^2_i, \sigma_{bn,i}^2)) + \alpha_{oh} \sum_i CE(z_{s,i}, \arg \max z_{s,i}) \tag{5}
\]

Here the first item in equation 5 is to align the statistical value of intermediate BN layers between the generated sample and real data, and the second item is designed to balance the distribution of different classes at the output space of the teacher model. Such design of \( L_\theta \) aligns the generated distribution with the original data distribution.

Different from the previous DFKD methods, we adjust the difficulty of generated samples by tuning the hyperparameter \( \alpha_{adv} \). Here we use a predefined function \( \alpha_{adv}(t) \), where \( \partial \alpha_{adv}(t)/\partial t \geq 0 \) to promote the increasing difficulty during training. The detailed design of \( \alpha_{adv}(t) \) and the effect for the performance is discussed in section V-E. The adjustment of the gradient of difficulty is presented as an orange dashed arrow in Fig. 1.

For the stage of training of student model \( \phi_s \), we also use the guidance of difficulty adjustment during training. As the discussion in section II-B, automatic CL dynamically adjusts the difficulty of the training process. According to [47], implementing CL by appropriate pacing function or transferring from the teacher can greatly improve both training speed and convergence during training. Therefore, in the setting of DFKD, the original domain is set as the pretrained teacher model, and thus provides a better scheduler for the guiding of DFKD.

Therefore, we implement self-paced learning with different strategies. According to equation 3, if we use explicit expression of \( g(\lambda, \nu) \), we get tractable optimal \( \nu^*(\lambda, L) \) by convex optimization. Therefore, the scheduler of \( \lambda \) is important. Here we define \( \lambda(t) \) as a linearly increase function with respect to epoch \( t \). Noticed that there are more adaptive design of \( \lambda(t) \) like active learning [59] or deep reinforcement learning [60]. We do not discuss them in this paper because it causes extra calculation, but we’ll discuss some other smarter designs in future works.

Reduce the parameter of \( \nu \) and \( \theta \) in equation 3, we get the objective function for optimizing \( \phi_s \) is,

\[
\min_{\phi_s} F(\phi_s) = \nu^*(\lambda, L)^T \mathbb{E}_{x \sim p_\theta}[D(f_s(x)|T, z_s(x; \phi_s)/T)] + g(\lambda, \nu^*)
\]

\[
= \sum_{i=1}^N \nu_i^*(\lambda, l_i) l_{i,\phi_s}(G_\theta(z)) + g(\lambda, \nu_i^*) \tag{6}
\]

Here \( z_s, z_s \) represent the logit output at the last layer of the teacher model and student model, and \( T \) represents
the temperature defined in original KD [1] to soften the output distribution of $\phi_t$ and $\phi_s$.  The second line of equation 6 is the implementation of the first line. Therefore, when updating $\phi_s$, the dynamic difficulty is computed by $v^*(\lambda, L) = E_{x \sim p_\theta(x)}[D(\pi_t(x)/T, \pi_s(x; \phi_s)/T)]$.

C. Does CuDFKD Really Converge?

Here we need to verify whether the AOS strategy can lead to the convergence of student model $\phi_s$. Assume the learned distribution of generated data is $p_\theta(x)$, here we find a proper parameter $\theta^*$ to generate easy-to-hard pseudo samples first, and the reweighting factor $v^*$ adjust the difficulty at a fine-grained level. Motivated by [41], the convergence of CuDFKD is analyzed by the following proposition, i.e.,

**Proposition 1 (Convergence of CuDFKD).** The objective function $F(\phi_s, v, \theta)$ is equal to the Majorization Minimization (MM) step for optimizing the following latent function:

$$F_\lambda(L(\theta, \phi_s)) = \int_0^L v^*(\lambda, L) dL$$

Thus using AOS promises the convergence of all parameters.

**Proof.** According to Theorem 1 in [41], and set parameter $w = (\theta, \phi_s)$ it is proved that

$$F_\lambda(L(w)) = Q(w|w^*) = F_\lambda(L(w^*)) + v^*(\lambda, L(w))[L(w) - L(w^*)]$$

for any $w^*$ and concave function $F$. Thus for the majorization step, the $\theta$ is fixed, and the $v^*$ is achieved by $v^*(\lambda, L(w)) = \arg\min_{v \in [0,1]} F(w, v)$, where $F(w, v)$ is defined in equation 1.

For the minimization step, setting $w^{k+1} = \arg\min_w Q(w|w^k)$, the update for $w = (\theta, \phi_s)$ is

$$w^{k+1} = \arg\min_w v^*(L(w^k), \lambda)^T L(w)$$

As the item loss function for student $L(w)$ is defined as $E_{x \sim p_\theta(x)}[D_{KL}(p_\theta(x)||p_\phi(x))]$, and $v^*$ is fixed, it’s equal to the objective function of KD. By the previous DFKD works, when setting data or diversity prior to DFKD model, AOS strategy promises convergence to optimize $w = (\theta, \phi_s)$.

According to MM theory [22], the lower bound of objective function on equation 8 are monotonically non-decreasing and thus promises convergence.

D. Does CuDFKD work well?

In this subsection we need to give a theoretical perspective on whether the easy-to-hard strategy improves the performance of DFKD. Noticing that CuDFKD does not perform enough well when distilling small neural networks, here we give a brief discussion on the results. From the VC theory of distillation [61]–[63], the error between the teacher and student of CuDFKD is bound by

$$R(f_s) - R(f_t) \leq O\left(\frac{|F_s|}{n^a} + \epsilon_t\right)$$

Here the $R()$ is the error of specific function, $f_s \in F_s$ is student function and $f_t \in F_t$ is teacher function, and both teacher and student function are related to approach an unknown target function $f \in F$, $\frac{1}{2} \leq \alpha \leq 1$ is related to the learning rate of the training model. Moreover, $\epsilon_t$ is the approximation error between the teacher function and student function. $F_s$ with respect to teacher function $f_t \in F_t$, and $n$ is number of data samples. In the setting of DFKD, the learning rate $\alpha$ is manually set by giving a learning rate $lr_s$ of KD training.

In CuDFKD, the estimation of training error is reweighted for the easy-to-hard strategy. For $L_{gb, st}$, the number of $n$ is batch size. Due to the easy-to-hard strategy and we choose the divergence $D(z_t, z_s)$ as the measurement of difficulty scheduler, $\alpha$ is close to $\frac{1}{2}$ and $\epsilon_t$ is small at an early stage, and $\alpha$ gradually increases and $\epsilon_t$ becomes larger at a later stage. Thus during training, it promises a low upper bound for the generalized error. When the student is small, $|F_s|_C$ also becomes small, and thus in the early stage if we generated easy pseudo samples, $L_{gb, sr}$ also becomes small. Therefore, the student model is closer to the teacher model at early training stage and more possibly traps into the local minima.

The above discussion presents that while updating $\phi_s$, CuDFKD can help student better approach teacher. Similarly, the error gap between teacher and target (ground truth) function is,

$$R(f_t) - R(f_s) \leq O\left(\frac{|F_t|}{n^a\alpha} + \epsilon_{tr}\right)$$

Thus the error gap between the target and student is calculated by adding equation 11 and equation 10, i.e.,

$$R(f_s) - R(f_t) \leq L_{gb, tr} + L_{gb, st}$$

For the item $L_{gb, tr}$, it’s only related to the training performance of the generator. The generation stage of CuDFKD finds the best sample for the teacher by the loss $L_{gb}$, and thus the $L_{gb, tr}$ is also low during training. Finally, it promises the low bound of $L_{gb, tr} + L_{gb, st}$ during training, and thus the better classification performance for the student model.

E. Relationship with the Memory-based DFKD Methods.

From the above discussion, the idea of CuDFKD is similar to the memory-based DFKD methods, because both consider the early student model and further improve the performance. In this subsection, we explore the theoretical difference between CuDFKD and memory-based methods [16], [17]. Typically, they use past information during generation to increase the diversity and catch the learned information at the early steps. In CMI and PRE-DFKD, they directly use extra memory to save the generated pseudo samples of the past epochs and thus help the small model learn better. Some other continual learning methods [64]–[66] use regularization...
TABLE II: The DFKD performance on CIFAR10 and different teacher-student pairs. All results are achieved from our implementation. Here WRN is in short of Wider ResNet. All chosen performances are the best performance during all runs of training. The metrics are defined in section V-A.

| DataSet | CIFAR10 |
|---------|---------|
|         | ResNet34 | VGG11 | ResNet18 | WRN-40-2 | WRN-40-1 | WRN-40-2 |
|         | Acc@1    | Agree@1 | Loyalty | Acc@1    | Agree@1 | Loyalty |
| Teacher | Student  |         |         | Teacher  | Student  |         |
| T.Scratch | 95.70    | 100.00  | 1.0000  | 92.25    | 100.00  | 1.0000  |
| S.Scratch | 92.22    | 93.20   | 0.7686  | 81.10    | 82.30   | 0.6303  |
| DAFL     | 96.10    | 95.33   | 0.8478  | 90.36    | 93.11   | 0.8063  |
| ZSKT     | 94.87    | 95.33   | 0.8478  | 90.42    | 90.91   | 0.7998  |
| ADI      | 94.87    | 95.33   | 0.8478  | 90.42    | 90.91   | 0.7998  |
| DFQ      | 93.26    | 96.46   | 0.8747  | 93.18    | 95.27   | 0.8440  |
| CMI      | 94.10    | N\A     | N\A     | 91.61    | 96.00   | 0.8267  |
| PRE-DFKD | 94.10    | N\A     | N\A     | 91.61    | 96.00   | 0.8267  |

CuDFKD (Ours) | 95.28 | 98.20 | 0.8915 | 91.61 | 96.00 | 0.8267 |

1 The results of PRE-DFKD in CIFAR10 and CIFAR100 are directly picked from their paper, for we cannot reproduce their performance successfully.

The results of PRE-DFKD in CIFAR10 and CIFAR100 are directly picked from their paper, for we cannot reproduce their performance successfully.

The implementation is based on the framework provided by the paper from CMI [16]. Please refer to supplementary material for detailed hyperparameters, the architecture of generators, and adversarial schedulers. Our implementation is presented in https://github.com/ljrprocc/DataFree.

To prove CuDFKD can improve the robustness and fidelity of the DFKD framework, we use metrics reported by [63], [72], i.e.,

- **Average top-1 accuracy** $\text{Acc}@1$. It’s widely-used for the measurement of the learning performance of student accuracy. It’s calculated by

  $\text{Acc}@1 = \frac{1}{n} \sum_{i=1}^{n} \delta((\arg\max_{j} z_{i,j}^{s}) = y_{i})$ (14)

- **Average top-1 agreement** $\text{Agree}@1$ [72]. It’s proposed to measure the generalization of KD framework, and it’s calculated by

  $\text{Agree}@1 = \frac{1}{n} \sum_{i=1}^{n} \delta((\arg\max_{j} z_{i,j}^{s} = \arg\max_{j} z_{i,j}^{t}))$ (15)

- **Average Probability Loyalty** $L_{p}$ [63]. It’s first proposed to measure the performance of model compression of BERT [52]. The probability loyalty measures the robustness of the learned distribution by the student model. It’s calculated by

  $L_{p}(P\|Q) = 1 - \sqrt{D_{JS}(P\|Q)}$ (16)

where $D_{JS}(P\|Q)$ is the JS divergence between the distributions of $P$ and $Q$.

Here $\text{Acc}@1$ is widely-used in previous DFKD methods [15]–[17], [73], but it only measures the divergence between the distribution of student logit $p(z^{s})$ and label distribution $p(y)$. As the pretrained teacher model is the only training target information for the setup of DFKD (discussed in Section I), the generalization error of DFKD is related to the gaps between teacher outputs and student outputs. Therefore, the metrics $\text{Agree}@1$ and $L_{p}$ can measure such gaps and thus better for the measurement of performance.
TABLE III: The DFKD performance on CIFAR100 and different teacher-student pairs. All results are achieved from our implementation. Here WRN is in short of Wider ResNet. Both chosen performance are the best performance during all runs of training. The metrics are defined in section V-A.

| DataSet     | ResNet34     | VGG11     | WRN-40-2 | WRN-40-2 |
|-------------|--------------|-----------|----------|----------|
| Teacher     | Student      |           |          |          |
| Teacher     | Student      |           |          |          |
| T.Scratch   | 78.05        | 71.32     | 75.83    | 75.83    |
| S.Scratch   | 73.24        | 73.24     | 64.87    | 66.61    |
| DAFL        | 67.58        | 64.49     | 55.06    | 55.48    |
| ZSKT        | 56.49        | 59.83     | 44.35    | 50.98    |
| Adj         | 69.13        | 68.21     | 52.25    | 51.54    |
| DFQ         | 72.06        | 69.37     | 66.61    | 64.87    |
| CMI         | 73.75        | 69.78     | 63.62    | 64.62    |
| PRE-DFKD    | 77.10        | 71.69     | 66.89    | 65.11    |
| CuDFKD(Ours)| 75.71        | 70.85     | 66.43    | 65.66    |

![Fig. 2: Distribution of probability loyalty $L_p$ for different DFKD methods. T: ResNet34, S:ResNet18, Benchmark: CIFAR100. Better viewed in color.](image)

B. Results and Analysis

In this subsection, we report the result and convergence of CuDFKD and some other discussion.

1) Results on Different Benchmarks: Table II and table III present the performance on different benchmarks and teacher-student pairs. The T. Scratch and S. Scratch denotes the training accuracy of the teacher and student model from scratch using the original training data. N/A presents that we cannot achieve the result from PRE-DFKD and only pick the value from their original paper. The $Agree@1$ and $L_p$ for the teacher model is 1.0 according to their definition. From table II, we observe that CuDFKD performs better than most methods including the non-memory methods in CIFAR10. What's more, the replay-based methods like CMI [16] and PRE-DFKD [17] need an extra memory bank or memory generator, while our CuDFKD only adds a scheduler for the training. For different teacher-student pairs in CIFAR10, we get the best performance overall metrics in Table II.

Considering the harder benchmarks, we also implement CuDFKD on Tiny ImageNet, and the result is presented in Table IV. Because Tiny ImageNet has a larger image resolution from $32 \times 32$ to $64 \times 64$, we achieve the hyperparameters of generator models from the original paper and freeze them, and further adjust the hyperparameter of curriculum strategy $v^*$. Moreover, we retrain the teacher model on the benchmark and then perform CuDFKD. For other DFKD methods, we use the same architecture of the generator as CuDFKD. In table IV, the results CMI and ADI don’t get reasonable performance in our implementation. The above reinterpretation shows that CurrKD has stable and good performance at more difficult benchmarks.

2) Robustness at the evaluation sets.: To evaluate the robustness and fidelity of CuDFKD, we also report the average Top-1 agreement and the average loyalty probability as $Agree@1$ and $L_p$. From table II and table III, we observe that 1) both $Agree@1$ and $L_p$ metrics are positively correlated with $Acc@1$. 2) CuDFKD achieves the best performance among all benchmark and student-teacher pairs. the best performance. 3) S. Scratch results achieved a more desirable $Acc@1$, but $Agree@1$ and $L_p$ were not good enough. Observation 1) shows that the performance of the student model in the DFKD task depends heavily on the degree of imitation of the teacher model. Observation 2) shows that the main reason for the


(a) The convergence for CIFAR10, the running epochs is 250.
(b) The convergence for CIFAR100, the running epochs is 300.

Fig. 3: Visualization of validation accuracy curves of different curves with different methods. Blue curve represents our CuDFKD, respectively. T: ResNet34, S: ResNet18. Better viewed in color.

The good results of CuDFKD is the full learning of the information in teacher, i.e., the fully imitation of teacher. Observation 3) shows that the process of approximation to the teacher model is also gradually achieved during the training of the student model. Such process means it’s close to the target distribution \( p(y) \). Thus, by measuring the \( \text{Agree}@1 \) and \( L_p \) metrics, we establish the importance of approximating the distribution determined by the teacher model for DFKD training and thus presents the superiority of our CuDFKD over previous methods.

To better understand the generalization performance of the DFKD results, we visualize the probabilistic fidelity distribution on the evaluation dataset. We visualize the \( L_p \) distribution for the last epoch of ADI, CMI and CuDFKD in CIFAR10 with teacher-student pairs as Wider ResNet 40x2 - Wider ResNet 40x1 pairs. Figure 2 shows the distribution results. It is clear that CuDFKD obtains more probabilistic loyalty than ADI and CMI on the benchmark of evaluating CIFAR10 and that there is a more explicit rightward shift of the first wave peak. This phenomenon is reasonable, meaning that ADI and CMI designed the loss function of the generator \( L_g \) with its added regularization term to increase the diversity of the pseudo-samples. It constructs a trade-off with the disagreement on the teachers, so that the similarity to the teachers is sacrificed for the generation the diversity samples.

For CuDFKD, the difficulty function is designed by the disagreement between teachers and students, and it changes dynamically with the training process. Therefore, it is more inclined to the imitation and learning process for teachers, and it has higher \( \text{Agree}@1 \) and \( L_p \). The performance of \( \text{Agree}@1 \) and \( L_p \) proves our guess that \( L_{gb, st} \) is low and high \( \text{Acc}@1 \) proves that the \( L_{gb, st} + L_{gb, tr} \) is low in equation 12.

In conclusion, CuDFKD reaches comparable results among the SOTA methods, because it better explores the global minimum during the easy-to-hard training strategy. Here the results are all achieved from the best checkpoint during training, we call this peak performance. For CuDFKD, we also care about it’s convergence and performance during the training stage.

3) Convergence of CuDFKD: In this subsection, we check the convergence of our framework compared with other SOTA methods by plotting the validation accuracy at each timestamp \( t \) (or epoch) during training. Fig 3 shows the convergence of ResNet18 with the teacher of ResNet34 under the hyperparameter given by the paper of each work with different benchmarks. Here we use \( \text{Acc}@1 \) as metric for this experiment. The curriculum used for this experiment is the same as the results in Table II. Here our CuDFKD converges fast and efficiently at a few epochs (less than 30 epochs to reach 90% top1 accuracy), and further improves till the end of training. Furthermore, the training process is stable, i.e., the validation accuracy during training does not disturb so much. Other previous work is not stable enough to get the final performance.

Quantitatively, we use the mean \( \mu[s_{acc}] \) and variance \( \sigma^2[s_{acc}] \) over all epochs of validation student accuracy motivated by PRE-DFKD [17]. Here we calculate the \( \mu[s_{acc}] \) and \( \sigma^2[s_{acc}] \) by the mean and variance of validation accuracy from the 80th epoch to the end. We choose 80th epoch because all the methods gradually move to convergence from that epoch. Besides, we also record the peak performance during training as well as the used GPU memory and training time. The results in Table V present the \( \mu[s_{acc}] \) and \( \sigma^2[s_{acc}] \) for all SOTA methods. From the results of Table V, our CuDFKD promises stability during the training of DFKD without any memory bank or replay generators, and higher \( \mu \) over all SOTA methods. The results of memory usage and time cost also show that our CuDFKD uses the memory usage as DAFL but gets significantly better performance.

Both quantitative and qualitative results present that CuDFKD are more stable than the memory-based CuDFKD problem, and thus provide more robustness of DFKD. In Table II and III, CuDFKD can outperform existing methods in most teacher-student pairs and in most metrics, but it still has some disadvantages compared to Memory-based methods, such as CMI in some small models and CIFAR100 benchmark. We consider that CuDFKD use predefined scheduler instead of external early samples to schedule the training process. Therefore, the performance of CuDFKD is limited to the design of difficulty measurer and training scheduler.

C. Difficulty Visualization at Different Stages.

In the design of CuDFKD, we use the divergence between the teacher and student models to define the difficulty. Then, during the training process, we need to determine whether the easy-to-hard criterion is satisfied throughout the training process. Here we need to explore the effect of this design on training student models. We visualize the distribution of sample difficulty for different training stages as well as the visualization of the samples. Combined with the definition of SPL, we focused on visualizing image \( X \) as difficulty. In addition, we compute the difficulty of the generated samples by computing \( y_t = \arg \max_i z_{ti} \). The experiments are trained on CIFAR100 with WRN-40-2 as the teacher and WRN-16-2 as the student, with a batch size of 1024.

The visualized samples are presented in Fig. 5. Fig. 5a shows the visualization results of the difficulty distribution (distribution B) for the 10th epoch as well as for the 30th epoch (distribution A). Fig. 5b and 5c show the visualization results of the same category of pseudo-samples for the 10th
TABLE V: The stability for the training of ResNet18 taught by ResNet34 on two CIFAR benchmarks. Here the $\mu$ and $\sigma^2$ achieved by CuDFKD are performed by 4 runs. The memory usage and training time tests are all performed on one NVIDIA 3090 GPU, and batch size of 256. Here we use $\text{Acc@1}$ as the metric.

| DataSet | $\mu$ | $\sigma^2$ | best Mem | Time | $\mu$ | $\sigma^2$ | best Mem | Time |
|---------|-------|------------|----------|------|-------|------------|----------|------|
| DAPL    | 62.5  | 17.1       | 92.0     | 6.45G| 6.60h | 52.3       | 12.8     | 74.5  | 6.45G | 7.09h |
| DFAD    | 86.1  | 12.3       | 93.3     | -    | -     | 54.9       | 12.9     | 67.7  | -     | -     |
| ADI     | 87.2  | 13.9       | 93.3     | 7.85G| 25.2h | 51.8       | 18.2     | 61.3  | 7.85G | 30.4h |
| CMI     | 82.4  | 16.6       | 94.8     | 12.5G| 13.3h | 55.2       | 24.1     | 77.0  | 12.5G | 22.3h |
| MB-DFKD | 83.3  | 16.4       | 92.4     | -    | -     | 64.4       | 18.3     | 75.4  | -     | -     |
| PRE-DFKD| 87.4  | 10.3       | 94.1     | -    | -     | 70.2       | 11.1     | 77.1  | -     | -     |
| CuDFKD  | 94.1  | 2.88       | 95.0     | 6.84G| 5.48h | 71.7       | 4.37     | 75.2  | 6.84G | 7.50h |

Fig. 4: Performance of using clean and noisy teacher for training CuDFKD. T: ResNet34, S: ResNet18, Benchmark: CIFAR10. Better viewed in color.

Fig. 5: Visualization of distribution of difficulty at different stages while training CuDFKD. T: WRN-40-2, S: WRN-40-1, Benchmark: CIFAR100. Better viewed in color.

epoch as well as for the 300th epoch. We can see that there are sharper peaks in distribution A at the beginning of training compared to distribution B, and the peaks in A are more to the left than those in B. The sharp peaks indicate that the samples are not sufficiently diverse at the beginning of the training phase, and therefore the visualization is not as effective. Similar results are obtained from the sample visualization results in Fig. 5b and Fig. 5c. For Fig. 5b, the samples between categories already possess a certain gap, however, the intra-class samples are more similar, and such setting for the samples can effectively help students learn quickly in the teacher model and achieve the learning process from easy to difficult as in Section I.

D. Comparable results on Noisy Teachers.

In the practical world, the pretrained teacher we achieve is always not correct enough, which means there is some noisy information in the teacher model. According to the previous works in curriculum learning [20], [43], the CL framework has better performance while the target information in the data is not clear. Therefore, we check how CuDFKD learns from the noisy teacher model. Here the noisy teacher is built by the insufficient training of scratch ResNet34 model. In this experiment, we use ResNet34-ResNet18 as the architecture of the teacher and student network, where the top1 accuracy of the teacher is only 94.07%. All experiments are performed by the batch size of 768. The results are from Fig 4. We run 3 experiments with random seed \{0, 10, 20\}, and report the error bar in Fig 4 of all three metrics.

From Fig 4, with the guidance of the noisy teacher, our CuDFKD model also achieves more than 93.3% top-1 accuracy, with less than 0.7 percentage drop with the teacher. Besides, CuDFKD can even improve the probability loyalty during training, it further proves that our CuDFKD is robust for some noise information in the teacher model. Such robustness is due to the dynamically reweighting of generated
samples, which provides another type of supervision for the student network.

From Fig 4 we have some other interesting discoveries. Firstly, DAFL drops a lot in all metrics, because DAFL does not consider the adversarial samples, and thus lacks robustness. Secondly, CuDFKD and CMI drop less than ADI and DAFL, because we use curriculum strategy and CMI uses memory to make better interaction between teacher and student models. Lastly, CuDFKD reports less variance than CMI during different random seeds, and even better probability loyalty while using the noisy teacher model. It presents that a good curriculum strategy can help the student learn knowledge from the teacher more efficiently and help align the output distribution from the teacher and student models. However, it can cause some potential drops in performance because it relies more on the performance of the teacher model. Training DFKD on the noisy teacher model is an interesting issue in future researches.

E. Ablation Study and Hyperparameter Searching

In this subsection, we check whether the CuDFKD is effective and compare different hyperparameters of a given design of $\nu^*$ and $L_\mu(x)$. We answer the following question, i.e., is curriculum learning works among different hyperparameter setting on different $\nu^*$ s?

Effect of Curriculum Strategy. For the choose of different forms of $\nu^*$, we design different forms of $\nu^*$s, i.e,

- **Hard** [21]: $\nu^*(\lambda, L) = I(L < \lambda)$
- **Soft** [53]: $\nu^*(\lambda, L) = 1(L < \lambda)(1 - L/\lambda)$
- **Logarithm** [29]: $\nu^*(\lambda, L) = 1 + e^{-\lambda}$

Here function $I()$ represents the indicator function. All experiments use the same experimental setting of other hyperparameters. Both experiments are implemented on the distillation of ResNet18 from ResNet34 on the benchmark of CIFAR10. Please refer to Fig 6 for final results.

The results match the same conclusion as previous curriculum learning works [20]. In Fig 6, we conclude that: 1) Whatever the curriculum strategy is, the validation accuracy of student has some improvements. 2) When we using softer curriculum strategy like logarithm scheduler, the learning performance greatly improves. It’s reasonable because the logarithm scheduler avoids the hard threshold like indicator function, which provides a continuous and differentiable objective function for the optimization of student network. Such continual settings help it find global minimum more efficiently.

Effect of $\lambda_0$. As is discussed in section IV-B, the hyperparameter $\lambda(t)$ greatly affects the actual curriculum strategy. When function $\lambda(t)$, it’s also important to find a proper $\lambda_0 = \lambda(0)$. It affects the initial reweighting of the generated pseudo samples, which also affects the beginning of the training of DFKD. Specifically, when $\lambda_0$ is too large, almost all the generated samples are included in the training and the SP-regularizer $g(v; \lambda)$ is close to zero, which collapses to the same training process as previous DFKD methods, called **overreweighting**. If $\lambda_0$ is too small, almost no samples are included in the training and most contribution to the objective function $F$ is $g(v; \lambda)$, which does not optimize student model intrinsically, called **underreweighting**. Thus in this experiment, we explore an appropriate $\lambda_0$.

In the experiment, we choose $\lambda_0 \in \{2, 2.2, 2.5, 2.8\}$ for brief exploration, as when $\lambda_0 < 2$ the framework becomes underreweighting and diverge quickly, and when $\lambda_0 > 3$ the framework becomes overreweighting. The experiments are performed at the logarithm strategy for $\nu^*$, and we use noisy ResNet34 as teacher and ResNet18 as student. Here we use noisy teacher model because we only explore the hyperparameter sensitivity of curriculum strategy. The result is shown in Fig 8. Here $\lambda_0$ is slightly negatively correlated with final performances, but all of them have more than 93% accuracy@1, which still performs better than other SOTA methods. For the metric of agreement@1 and probability loyalty, it presents the similar phenomena to accuracy@1. It
generations. Here we implement the comparison on the benchmark of CIFAR100, with VGG11-ResNet18, ResNet34-ResNet18, and WRN-40-2-WRN-40_1 network pairs. Both experiments are performed with batch size of 768 for better results, and we use a simple scheduler as
$$
\alpha_{adv}(t) = \begin{cases} 
0, & t \leq k_{begin}N \\
\alpha \cdot \frac{t}{N}, & k_{begin}N < t \leq k_{end}N \\
\lambda_{adv, final}, & t > k_{end}N 
\end{cases} 
$$
(17)

Here the epochs from 0 to $k_{begin}N$ is called warm-up stage in previous works [17]. To avoid adding too much noise into the pseudo samples, we set $k_{end} < 1$. Therefore, we adjust $k_{begin} \in \{1/5, 1/4, 1/3\}$ and $k_{end} \in \{2/3, 3/4, 4/5\}$ for hyperparameter searching, and $N$ is the total training epochs. The results are presented in Fig 9. From the result we can see that $k_{begin}$ is more sensitive than $k_{end}$, and all the best performance are from $k_{begin} = 1/5$. In lighter networks like wider ResNet series, $Acc@1$ changes more than $Agree@1$ and $L_p$.

### Gradient of adversarial item $\alpha$
From Equation 17, we can see that the gradient parameter $\alpha$ of $\lambda$ growth is the key parameter controlling the difficulty variation, so its effect on
DFKD needs to be further explored. The value of $\alpha$ greatly affects the effectiveness of the difficulty scheduler. Here we set $\alpha \in \{0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4\}$ on CIFAR100 for comparison experiments. The results are shown in Fig 10.

It’s obvious that as $\alpha$ increases, all three metrics show a similar trend of first increasing and then decreasing. When $\alpha$ is too low, the change in difficulty is not significant and thus the training process degenerates into ordinary DFKD. When $\alpha$ is too large, the late stage of training generates a large number of samples near the decision boundary and thus tends to make it more difficult to capture the information of image contained in the classification.

**Temperature $T$ for KD.** In the previous KD framework, the temperature $T$ has the role of smoothing the output distribution of the model and helping to align the teacher and student models across the distribution. And in our experiments, we found that different model architectures need to set different temperatures $T$. Therefore, we set up several comparison experiments combining several $T$ values commonly found in full-data KD and DFKD, and report the variation of the three metrics with $T$. The experimental results are in Fig 7.

From Fig. 7, we can see that when the model architecture is ResNet series and VGG series, taking a larger $T$ value compared to full-data KD ($T = 4$) will show better results. Moreover, smoother output for heavier models is required to obtain better KD results.

**VI. CONCLUSION AND FUTURE WORKS**

In this paper we propose a simple but effective DFKD framework combined with self-paced learning(SPL), called CuDFKD, and further make a systematic exploration of the design of DFKD. Different from previous DFKD methods, our CuDFKD uses dynamic difficulty with the timestamp of training process as a target information for the generation of pseudo samples. By SPL, we dynamically adjust the difficulty of generated samples. Then we analyze that CuDFKD promises the convergence of all parameters due to MM theory. Practically, we implement AOS strategy, and dynamically add the weight of adversarial samples on the training of generator. In the experiment, we achieve the best performance of DFKD over some replay-based methods, and the convergence of CuDFKD is fast and stable. CuDFKD also performs well over a wide range of hyperparameter settings. In conclusion, CuDFKD provides a new perspective on how to dynamically distill from teacher and what type of knowledge can help improve the training of KD.

However, there still some limitations of CuDFKD left for the future work. Firstly, the scheduler $\sigma_{adv}(t)$ is designed manually by choosing the best validation accuracy on all the experiments. We’ll further improve it by more automatic strategies. Secondly, the curriculum setting of matching $\nu^*(\lambda, L)$ and $d(p_{0}(z), t)$ can be more flexible. Furthermore, we can combine sequential deep generative models with CuDFKD for future works to help control the difficulty of generated samples at different timestamps.

**VII. ACKNOWLEDGEMENT**

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VIII. Biography Section

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