Conditional Generative Data-Free Knowledge Distillation based on Attention Transfer

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Abstract

Knowledge distillation has made remarkable achievements in model compression. However, most existing methods demand original training data, while real data in practice are often unavailable due to privacy, security and transmission limitation. To address this problem, we propose a conditional generative data-free knowledge distillation (CGDD) framework to train efficient portable network without any real data. In this framework, except using the knowledge extracted from teacher model, we introduce preset labels as additional auxiliary information to train the generator. Then, the trained generator can produce meaningful training samples of specified category as required. In order to promote distillation process, except using conventional distillation loss, we treat preset label as ground truth label so that student network is directly supervised by the category of synthetic training sample. Moreover, we force student network to mimic the attention maps of teacher model and further improve its performance. To verify the superiority of our method, we design a new evaluation metric is called as relative accuracy to directly compare the effectiveness of different distillation methods. Trained portable network learned with proposed data-free distillation method obtains 99.63%, 99.07% and 99.84% relative accuracy on CIFAR10, CIFAR100 and Caltech101, respectively. The experimental results demonstrate the superiority of proposed method.

1. Introduction

In past few years, deep leaning based on convolution neural networks (CNNs) has been widely used to achieve state-of-the-art performances in various computer vision applications, such as image classification [1, 2], object detection [3] and semantic segmentation [4], and the number of CNNs-based applications has exploded. These techniques are employed in all walks of life from automatic driving [5] to cancer detection [6], from facial beauty [7] to games intelligence [8].

Actually, the superior performance of deep learning came with over-parameterized convolution neural networks, which trained on large datasets. The pre-trained network enables extracting salient features of the data automatically for a target task and ensures generalization. In other words, the success of deep models heavily rely on heavy computation and storage as well as a large number of human annotations. However, ever-growing model parameters and computational cost inhibit the application of high-performance models on cloud and edge devices. In particular, memory requirements and computational costs are critical factors that need to be considered carefully for efficient inference when we deploy the pre-trained models on resource-limited platforms. In this case, model compression is an important step in developing efficient models. Recent years, various effective methods have been proposed to compress and speed-up pre-trained heavy deep models, including network pruning [9, 10, 18, 19, 20], parameter quantization [11, 12, 21, 22, 23, 24], low-rank decomposition [13, 14] and knowledge distillation [15, 16, 17, 25, 26, 27].

Among these methods, parameter quantization and low-rank decomposition can reduce the computational cost and memory requirements without altering the network architecture. Specifically, network pruning could compress a heavy model by removing redundant weights and filters that have less information. Typical pruning works either prune the filter weights to obtain sparse weight matrices (weight pruning) [9], or remove entire filters from the networks (filter pruning) [10, 18, 19, 20]. Prior art on filter pruning can be grouped into two categories: pre-defined architecture [10, 18] and learned architecture filter pruning [19, 20], which depends on whether the architecture of pruned network is assumed to be given. Different from network pruning, parameter quantization compresses a cumbersome network by reducing the number of bits required to represent parameter values. In CNNs, network parameters include weights, activation, gradient and discrepancy, and most parameter quantization works achieve model compression by reducing the accuracy of network weights. Through quantization, network parameters can be converted from 32-bit floating point (FP32) towards 16-bit [21] or 8-bit [22], with minimal loss of accuracy. In addition, there are even techniques that directly train the networks with binary weights (single bit

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In deep neural networks, convolution computation is the most complicated computation operation, so that we can compress the models by low-rank decomposition. The core idea of low-rank decomposition [13, 14] is using matrix or tensor decomposition techniques to estimate and decompose the filters in deep models. Low-rank decomposition can realize model compression and acceleration without changing the network structure, as does parameter quantization.

Knowledge distillation (KD) is a knowledge transfer framework to train a small “student” network under the supervision of a large pre-trained “teacher” network. KD could compress models in spite of the difference of network structure and has broad applications in Computer Vision (CV), Natural Language Processing (NLP), etc. According to different taxonomy methods, existing KD approaches can be classified into different categories. Based on the number of teacher networks, KD can be grouped into distillation from one teacher [15, 16, 17] and distillation from multiple teachers [25, 26, 27]. According to the source of transferred knowledge, we can classified existing KD methods into logit-based distillation [15] and feature-based distillation [16, 17]. KD is very efficient for compressing cumbersome models when the original or alternative training data are available. However, training datasets for the given model in real-world applications are often unavailable due to privacy, security and transmission limitations. For instance, most users do not want their electronic records that containing private information to be leaked to others. Moreover, some training datasets are too huge to upload to the cloud in time. In this case, conventional model compression methods cannot be directly used for learning compact and efficient deep models.

For this issue, an effective way is using generated samples as training data and achieve data-free knowledge distillation [28, 29, 30, 31]. Recent years, a number of data-free (zero-shot) knowledge distillation methods that exploit GAN have been proposed for compressing deep models without real training data. In practice, due to the absence of real data, conventional generation techniques such as GAN [32] and VAE [33] cannot be directly applied on data-free KD. To address this problem, Chen et al. [29] design a novel framework to train a generator to create one-hot images, which can highly activate the neurons in teacher network. Fang et al. [30] propose an adversarial distillation mechanism to move the generated samples towards areas where the current student has not been well trained.

Although the existing works have basically realized data-free knowledge distillation, there is still a gap between the performance of the trained student and pre-trained teacher networks. Also, the trained generator can only produce images randomly, but cannot control the class of synthetic images. In this case, the synthetic images are class-balanced and may incompatible with long-tailed distribution tasks. For these problems, we proposed our conditional generative data-free knowledge distillation method. To be specific, we introduce preset labels as ground truth labels to guide the training of generator and make the generator can produce images of a specified class rather than random classes. Since the category of generated images is determined by preset label, student network can be trained under the supervision of ground truth labels (preset labels) when using the synthetic images as training data. With the supervision from ground truth label, we narrow the discrepancy between data-free and data-driven distillation methods. Furthermore, to reduce the performance gap between student and teacher network, we force student network to mimic teacher’s attention maps to improve student performance.

With the absence of real training data, we adapt the
idea of generative adversarial network to attain efficient data generation and propose our conditional generative data-free distillation framework, as illustrated in Figure 1. We aim to train a strong generator by exploiting the latent knowledge from pre-trained teacher network, and then use the generator to produce meaningful samples as training data to train the student model. To demonstrate the effectiveness of proposed method we conduct extensive experiments on several datasets, including MNIST, CIFAR10, CIFAR100 and Caltech101. We also perform a series of ablation experiments to analyze different components in this method. The main contributions of this paper can be summarized as follows:

We propose a conditional generative data-free distillation framework, which could consistently and efficiently produce meaningful samples for knowledge distillation.

We introduce auxiliary class constraint to train the generator and convert the optimization of generator into a semi-supervised process.

By transferring teacher’s attention maps to student network, we greatly improve the performance of student model.

We propose relative accuracy to directly compare the effectiveness of different methods and to avoid the impact of different evaluation criteria.

Extensive experiments on several datasets show the superior performance of proposed method compared to existing data-free knowledge distillation methods.

2. Related Work

In this section, we briefly review existing works on related topics.

2.1 Knowledge Distillation (KD).

Knowledge distillation is a general technique that can be used for model compression. It refers to the method that helps the training of a smaller student network under the guidance of a teacher network. KD can compress a network regardless of the structural difference between student and teacher networks. To be specific, it transfers the knowledge from a pre-trained teacher model to student model by forcing student to mimic the output of teacher model (including teacher’s logits and hidden layer features).

In KD, the knowledge could be transferred by minimizing the difference between logits (the inputs to the last SoftMax layer) produced by student and teacher networks. In many situations, however, the output of teacher network has very high probability at correct class, while the probabilities at other classes were very close to zero, since the output has been converted by a SoftMax layer. In this case, the logits could not provide more information than one-hot label. To tackle this problem, Hinton et al. [15] introduced the concept of “SoftMax temperature”, which can soften the output of network. This process can be formulated as:

$$q_{i} = \frac{\exp(l_{i} / \rho)}{\sum_{j} \exp(l_{j} / \rho)}$$ (1)

where $l_i$ are the logits of networks, $\rho$ is SoftMax temperature. When $\rho$ approaching 0, the output produced by SoftMax layer converges to a one-hot vector. If $\rho = 1$, it will be a standard SoftMax function. As $\rho$ increases, the probability distribution of output will become more softer, and it can provide more information about the relationships between different categories. With the SoftMax temperature, student network can be optimized using the following loss function:

$$L_{KD} = \frac{1}{n} \sum_{i} KL(q_{s}, q_{t})$$ (2)

where KL is Kullback-Leibler Divergence (KLD), $n$ is the number of samples, $q_{s}$ and $q_{t}$ are the softened outputs of student and teacher networks.

Moreover, for the images with ground truth label, it is beneficial to train the student network together with soft labels (logits) and ground truth labels. At this time, student network can be trained with the supervision of the ground truth labels. By adding the loss between student’s predicted labels and ground truth labels, we can update Equation 2 as:

$$L_{KD} = \frac{1}{n} \sum_{i} [KL(q_{s}, q_{t}) + \alpha KL(q_{s}, y')]$$ (3)

where $y$ is ground truth label, $\alpha$ is scale weight that trade-off different loss functions.

Besides the logits from teacher network, transferring knowledge to student network can be achieved using feature information [16, 17] from hidden layers. Romero et al. [16] proposed FitNets to train student network using not only the outputs (logits) but also the intermediate features learned by teacher network to improve student performance. Zagoruyko et al. [17] improve the performance by forcing student to mimic teacher’s attention maps. Although there are many different knowledge distillation methods, it is still hard to say that they are already the best. It remains very important to explore more efficient knowledge representation and utilization methods. Furthermore, although KD can downsize a network regardless of the structural difference, some recent works have explored the effect of structure on distillation performance [34, 35] and made some progress. For an overview of general distillation methods, we recommend the reader to read some reviews, such as [36].

2.2 Generative Adversarial Networks (GAN)

In order to transfer knowledge from teacher to student network without real training samples, we adapt the idea of generative adversarial networks to attain efficient data generation. Generative adversarial network [32] is a deep learning framework that learn to produce meaningful samples. It contains two interacting neural networks: a generator $G$ that captures the distribution of real data, and a discriminator $D$ to distinguish the real and fake samples.
The two networks are trained jointly through a minimax game: the discriminator aims to distinguish generated samples from real ones while the generator is dedicated to generating more realistic and indistinguishable samples to fool the discriminator.

To be specific, given a set of random noise vectors $z$ sampled from distribution $p_z$, $G$ maps $z$ to the distribution of desired data $x$, i.e. $G : z \rightarrow x$. $D$ outputs a high score (close to 1) for real sample and produces low probability (close to 0) for generated sample. The optimization procedure can be formulated as:

$$
\min_G \max_D V(D,G) = E_{x \sim p_{data}}[\log D(x)] + E_{z \sim p_z}[\log (1 - D(G(z)))]
$$

(4)

where $x$ is real sample and $G(z)$ is generated data. In early training stage, $G$ is too poor to craft realistic images, and $D$ can reject the generated images with high confidence. In this case, we can train $G$ to maximize $\log D(G(z))$ rather than minimize $\log (1 - D(G(z)))$ to avoid $\log (1 - D(G(z)))$ saturates. With the adversarial training, $G$ can generate meaningful data that match the real data distribution. Moreover, in order to make the generator could produce images of specified class, Mirza et al. [37] proposed the conditional GAN, which can be constructed by applying classes condition to both the generator and discriminator. To avoid the problem of training instability and mode collapse in conventional GAN, Arjovsky et al. [38] proposed Wasserstein GAN (WGAN) to train model more stable, and Qi et al. [39] use Lipschitz regularization to regularize the adversarial loss.

Since GAN was proposed, it has demonstrated powerful capabilities in image translation [40], super-resolution [41], restoration [42], etc. The powerful capabilities theoretically could be applied for data-free sample generation and then realize data-free knowledge distillation. However, while GAN is able to generate very realistic images, all these methods require real data to train the generator. In this case, it is significant to explore the implementation of GAN when real data is unavailable.

### 2.3 Data-free Model Compression.

Due to data privacy and security issues, real training data is often unavailable in the real world, and data-free model compression has been a hot topic and draw more and more attention in recent years. To tackle this problem, many data-free compression techniques have been proposed, including data-free network pruning [43, 44], parameter quantization [45, 46, 47] and knowledge distillation [28, 29, 30, 31, 48]. Srinivas et al. [43] first proposed a data-free pruning method that directly merge similar neurons in fully-connected layers. Tang et al. [44] presented a data-free model compression and acceleration method based on generative adversarial networks. Meanwhile, several studies quantified and fine-tuned the cumbrous models without any original data. DFG [45] improved data-free quantization performance by equalizing the weight ranges of each channel in network and correcting biased quantization error. ZeroQ [46] reconstructed training samples from random noises according to Batch Normalization Statistics of full precision models. Inspired by the idea of utilizing intermediate feature maps, ZAQ [47] proposed Channel Relation Map (CRM) to gain intermediate inter-channel discrepancy. It facilitates effective knowledge transfer from full-precision model to the quantized model.

In data-free knowledge distillation, Lopes et al. [28] first attempted to reconstruct original training data from “metadata” and utilized the synthetic data to train student network. However, this method still requires “metadata” that extracted from real data. Nayak et al. [48] proposed to model the SoftMax space as a Dirichlet distribution and update random noise images to craft Data Impressions. Chen et al. [29] designed a novel framework (DAFL) to train the generator to approximate original training data. In DAFL, the teacher model was fixed as discriminator, since it has already been well trained on large scale datasets and can well extract semantic features from images. However, the output of teacher is category of images instead of image’s quality, so the vanilla loss function in GAN framework fails. To this end, DAFL designed several new loss functions to guide the optimization process of generator. In contrast, Fang et al. [30] presented an adversarial distillation mechanism (DFAD) to craft a portable student network. In DFAD, student and teacher models jointly play the role of discriminator. They train student network to reduce the discrepancy between them, while training the generator adversarially create “hard samples” to enlarge the discrepancy. To achieve data-free distillation on large-scale datasets, Luo et al. [31] proposed a new approach (LSGD) to train generator by leveraging the intrinsic Batch Normalization Statistics of pre-trained teacher model. They train one generator for each class to avoid mode collapse (generator produces similar images and thus loses the diversity of real images) in image generation. This approach gets remarkable performance gain, but requires huge computational resources.

The methods mentioned above have basically realized data-free distillation, but there is still a gap with data-driven compression methods. In addition, the trained generator cannot produce images of the specified category as required. To this end, a more efficient approach for data-free distillation is required.

### 3. Method

In this section, we will describe the details of proposed conditional generative data-free distillation framework. Given a pre-trained teacher network $T$, a smaller student network $S$, and generator $G$. Inputting a set of random noise $Z = \{z', z'', ..., z'\}$ into the generator to produce training samples $G(z')$, where $z' \in R^n$ is sampled from normal distribution $p_z$. Note that in data-free knowledge distillation, no original training data is required.

#### 3.1 Data-free Conditional Generator

As mentioned above, original training data for given teacher are often unavailable for various concerns. To address this problem, the viable approach is using
alternative data [49] or irrelevant data to train student network. However, collecting a large amount of alternative data is still onerous, while irrelevant data will drastically deteriorate the performance of student network due to data bias. In this case, an effective way to avert this problem is reconstructing data by exploiting information from pre-trained teacher network. When training a model, the model will extract enough information from data to make decision. In other worlds, the pre-trained model contains rich knowledge about original training datasets. However, it is difficult to exploit the knowledge hidden in teacher model to reconstruct meaningful synthetic data. To this end, we adopt the mechanism of GAN to produce training data.

In vanilla GAN, we need real images as imitation object of generator, and discriminator learn to tell true from false. But now, real data is unavailable, so we design following several loss functions to guide the training process of generator.

**Classes Matching Loss (CM)**

In existing data-free distillation methods, the trained generators can only randomly produce images and cannot control the categories of generated images. The probability of generators generating each class of images is equal, so the synthetic training images are class-balanced. Class-balanced synthetic data is desirable for ordinary teacher model which trained on class-balanced datasets. But for the teacher network which trained on long-tailed datasets, it may cause special design for long-tailed data fails, and result in a poor performance of distillation. To this end, we introduce preset class labels as auxiliary information to build a conditional generator. Under the supervision of classes condition, trained generator can produce images of specified category on request and meet different requirements. Moreover, adding classes condition is equivalent to adding new constraints to the generator, which can optimize the generator better.

To be specific, we introduce preset class labels \( y \) as auxiliary information to guide the generator training following CGAN [37]. \( \{ y' \} \) are uniformly sampled from \( \{0,1,...,c-1\} \), \( c \) is the number of classes. The classes matching loss can be formulated as:

\[
L_{\text{CM}} = \frac{1}{n} \sum_{i=1}^{n} H(\text{softmax}(l'_i), y')
\]  

(5) 

where \( y' \) is preset label of \( i \) th image, \( H(\cdot) \) denote cross-entropy loss, \( l'_i = T(G(z | y)) \). This loss function calculates cross-entropy loss between the SoftMax outputs of teacher and preset labels. It is minimal when predicted results are same as preset labels. When teacher network is fixed, we can force generator to craft images according to preset class by reducing the loss function. Furthermore, we transform the training process of generator from unsupervised to a semi-supervised process by introducing this loss (the unsupervised loss will be introduced later).

**Unsupervised Loss (US)**

In data-free distillation, given a teacher model as discriminator, teacher output is image class instead of authenticity. Therefore, the vanilla loss function in GAN is inapplicable for imitating original datasets. Although we design classes matching loss as supervision, it is still difficult to train the generator from scratch. In this case, we use unsupervised loss following DAFL [29] to help the generator training.

To measure the class balance of generated images, DAFL introduced information entropy loss and this function is complementary to classes matching loss function in Eq.5. We define information entropy loss as:

\[
L_e = -H_{\text{inf}}(\bar{p}) = -\frac{1}{c} \sum_{i=0}^{c} \bar{p}_i \log(\bar{p}_i)
\]  

(6) 

where \( \bar{p} = \frac{1}{n} \sum l'_i \) is the average logit of all samples, \( H_{\text{inf}}(\cdot) \) is information entropy. When this function takes the minimum, every element in \( \bar{p} \) would equal to \( 1/c \). In this case, we can force the generator to produce a balanced set of synthetic samples by minimizing this loss function. Moreover, for a general classification task where the number of images for each category in training dataset is balanced, we can use this function together with Eq.5 to jointly promote the class-balance of generated samples. But if original data is class-imbalanced, we should discard this function and only use classes matching loss (in Eq.5) to constrain the category of synthetic images.

Besides information entropy, teacher output is also important information of input images. In classification task, trained teacher produces one-hot like vectors for input images. If synthetic samples follow the same distribution as original training data, teacher model will also output one-hot like vectors. In other words, if teacher network output a one-hot vector, the input image is likely to match original data distribution. To this end, we use one-hot loss to train the generator and define one-hot loss as:

\[
L_{\text{oh}} = \frac{1}{n} \sum \text{Cross}(l'_i, y'_i)
\]  

(7) 

where \( y'_i = \arg \max(y(l'_i)) \), \( l'_i \) is predicted label of teacher model. With supervision of one-hot loss, we can force generator to craft images that matching original training dataset. This loss function can be used simultaneously with classes matching loss (Eq.5) to help the generator training: Eq.5 requires the synthetic image to be a specified category, while Eq.7 pursues the image have more prominent feature of a certain category.

The above functions have no clear optimization objective, so we combine them as unsupervised loss:

\[
L_{\text{us}} = L_{\text{oh}} + \lambda_{\text{oh}} L_e
\]  

(8) 

where \( \lambda_{\text{oh}} \) is scale weight for balancing the different components.

**Batch Normalization Statistics Loss (BNS)**

The above functions acquire different knowledge about training data through various approaches, but all the knowledge is obtained indirectly from teacher output. In fact, batch normalization layer [50] used in most convolutional neural networks contains rich statistical
information about original training data. In this situation, we can use the statistics in batch-norm layers as constraint to guide generator to imitate real data. Therefore, we define batch normalization statistics loss as:

$$L_{bn} = \frac{1}{L} \sum_{i=0}^{L-1} \left( \| \bar{\mu}_i - \mu_l \|^2 + \frac{1}{L} \sum_{i=0}^{L-1} \| \bar{\sigma}_i - \sigma_l \|^2 \right)$$  \hspace{1cm} (9)$$

where $L$ is the number of exploited batch-norm layers, $\bar{\mu}_i / \bar{\sigma}_i$ denote mean/standard deviation of generated images at $i$th batch-norm layer, $\mu$ and $\sigma$ are the statistic information of real data that stored in pre-trained teacher model.

Discrepancy Estimation Loss (DE)

Loss functions mentioned above only use the knowledge from teacher model to constrain generator, and without any information from student network. In data-free distillation, however, student network will train together with generator. In this sense, the introduction of information from student model as supervision is beneficial for generator to craft images that compatible with student model. In order to utilize information from student network, we introduce the discrepancy estimation loss of student and teacher predicted results for synthetic images.

In DFAD, Fang et al. [30] stated that KLD and Mean Square Error (MSE) will produce gradient decay when student network converges on synthetic images. Then gradient decay will deactivate the learning of generator and make the minmax game over. In this work, we use Mean Absolute Error (MAE) of two network outputs as discrepancy estimation loss:

$$L_{de} = E_{z,p(z)} \left[ \frac{1}{n} \| T(G(z \mid y)) - S(G(z \mid y)) \|_2 \right]$$  \hspace{1cm} (10)$$

where $T(G(z \mid y))$ and $S(G(z \mid y))$ are the output of teacher and student networks for synthetic image $G(z \mid y)$.

Generally speaking, we hope the synthetic images will enable student model producing same predictions as teacher model, and now the discrepancy between them is minimal. In fact, however, if we use this function as the optimization objective of generator, it may cause generator tend to produce “easy samples”. When we use “easy samples” as training data, student network can easily learn to produce same predictions as teacher and minimize discrepancy estimation loss. But now, student network can only learn the shallow knowledge of teacher, and cannot learn deep latent knowledge by exploring “hard samples”. To tackle this problem, we conversely maximize this loss to move generator towards the areas where current student network has not been well trained. In this situation, generator will consistently produce “hard samples”, and student model can continuously explore unseen regions and achieve better performance. We will analyze this loss function together with adversarial distillation loss in Section 3.2.

3.2 Distillation Process

In distillation process, we use generator $G$ to craft a set of images $G(z \mid y)$ as training data. Then we fix teacher network $T$ and only update student network $S$. With the supervision of teacher model, the student network learns to extract image features to make decisions. To achieve efficient distillation, we introduce several loss functions to guide the optimization of student network.

Adversarial Distillation loss (AD)

In section 3.1, we introduce discrepancy estimation loss to measure the difference between the outputs of teacher and student networks. Following DFAD, we transform the training process of student and generator into an adversarial training framework. This framework contains generation process and distillation process. In generation process, we maximize discrepancy estimation loss to make generator learn to produce “hard samples” that difficult for both teacher and student networks to distinguish. In distillation process, we train student network by conversely minimizing this loss function. To distinguish it from the discrepancy estimation loss in section 3.1, we re-define it as an adversarial distillation loss:

$$L_{ad} = L_{ge} = E_{z,p(z)} \left[ \frac{1}{n} \| T(G(z \mid y)) - S(G(z \mid y)) \|_2 \right]$$  \hspace{1cm} (11)$$

To minimize adversarial distillation loss, student network will learn the hidden knowledge of teacher model and produce the same output as teacher network.

Ground Truth Loss (GT)

In data-driven distillation method, if there is ground truth label in datasets, we can use it as constraint to optimize student network, as shown in Eq.3. In data-free distillation task, however, real data and ground truth label are unavailable so that the constraint failure. To facilitate distillation process and narrow the gap between data-free and data-driven distillation methods, we use preset label in conditional generator as ground truth label and define ground truth loss as:

$$L_{gt} = \frac{1}{N} \sum_{i=0}^{N} H(\text{softmax}(l_{s}^i), y^i)$$  \hspace{1cm} (12)$$

where $H(\ast)$ is cross-entropy loss, $l_{s}^i = S(G(z^i \mid y^i))$ is logit of student network. Different from Eq.5, here we calculate the cross-entropy loss between student network outputs and preset labels. By introducing this loss, student network can be optimized under supervision from the ground truth labels of training data.

Attention Transfer Loss (AT)

In this work, we found simple models can be well optimized with the loss functions mentioned above, but it is difficult for student to learn useful knowledge from a super strong teacher network with ordinary distillation methods. In this situation, data-free distillation with a strong teacher network is even more difficult due to the absence of real training data. To facilitate distillation process, we introduce attention transfer loss function. In natural world, attention plays a critical role in human visual experience, and it lets a system attend to an object
and examine it with greater detail. In neural network, attention maps show the area that model focus on, and it is the embodiment of the model’s ability to extract features. Following [51], we define activation-based attention maps as follows:

$$F(A) = \sum |A_i|^2$$  \hspace{1cm} (13)

where $A$ denote activation of each channel, $C$ is the number of channels, power and absolute value operations are element-wise. Then we formulate attention transfer loss as:

$$L_{at} = \sum_{j=1}^{I} \left\| \frac{Q_j^i}{\|Q_j\|_2} - \frac{Q_j^e}{\|Q_j\|_2} \right\|_2$$  \hspace{1cm} (14)

where $Q_j^i = \text{vec}(F(A_j^i))$ and $Q_j^e = \text{vec}(F(A_j^e))$ are the $j$th pair of student and teacher attention maps in vector form, $I$ is the number of layers that we choose to perform attention transfer. By minimizing this function, we can force student network to mimic teacher’s attention map and obtain better performance. Furthermore, KD position of the selected layers is very crucial in practical work, and it has a great influence on the final performance. To this end, we will do some work in this field in future.

### 3.3 Optimization Process

In this work, the conditional generative data-free knowledge distillation algorithm includes three networks: a pre-trained teacher network $T$, a student network $S$, and a generator $G$, the training procedure can be divided into two stages. In whole training procedure, we fix teacher network and alternately repeat training student network and the generator.

#### Train the Generator $G$

In first training stage, we train generator to craft meaningful samples which have same distribution as original training data. Also, we maximize discrepancy estimation loss to move the generator toward unseen areas to consistently produce “hard samples”. In this process, we random sample a set of vectors $\{z_i\}$ from Gaussian distribution $N(0,1)$, and uniformly sample preset labels $\{y_i\}$ from list $\{0,1,...,c-1\}$. Then we input the vectors into generator $G$ to produce fake samples $G(z \mid y)$. Combining the loss functions of conditional generator that described above, we define the optimization objective of generator as follows:

$$L_G = -L_{gc} + \lambda_{gt}L_{ct} + \lambda_{cs}L_{ct} + \lambda_{gs}L_{cs}$$  \hspace{1cm} (15)

where $\lambda_{gt}$, $\lambda_{cs}$ and $\lambda_{gs}$ are hyper-parameters for balancing different loss terms. In this stage, we only update generator’s parameters through back-propagation.

#### Train the Student Network $S$

In second training stage, we use generated samples $G(z \mid y)$ as training data to update student’s parameters. To be specific, we minimize distillation loss to make student network to mimic teacher network and achieve better performance. The final distillation loss can be formulated as:

$$L_{kd} = L_{id} + \lambda_{gt}L_{ct} + \lambda_{cs}L_{ct}$$  \hspace{1cm} (16)

where $\lambda_{gt}$ and $\lambda_{cs}$ are trade-off hyper-parameters. Different from the training of generator, we update student’s parameters $\lambda$ times in each epoch to ensure its convergence.

During the whole adversarial distillation process, generator $G$ continuously produce meaningful samples, and student model $S$ consistently learn useful knowledge from teacher network through distillation approach. The proposed conditional generative data-free knowledge distillation framework for learning efficient portable network is summarized in Algorithm 1.

#### Algorithm 1: Conditional Generative Data-Free Distillation

**Input:** A given pre-trained teacher network $T$ and hyper-parameters for balancing different terms.

**Output:** Student network $S$ and generator $G$

1. Initialize student network $S$ and generator $G$

2. **Repeat:**

3. **1. Train the Generator**

4. Random sample a set of random noise vectors $\{z_i\}_{i=1}^{n}$ and preset labels $\{y_i\}_{i=1}^{n}$;

5. Generate training samples $G(z \mid y)$;

6. Calculate the loss of generator $L_G$ (Eq.15);

7. Update parameters in generator $G$ according to the gradient;

8. **2. Train the Student Network**

9. for $k$ iterations do:

10. Sample noise vectors $\{z_i\}_{i=1}^{n}$, and preset labels $\{y_i\}_{i=1}^{n}$;

11. Generate training samples $G(z \mid y)$;

12. Compute the distillation loss $L_{kd}$ (Eq.16)

13. Update parameters in student network $S$ using back-propagation;

14. end

15. **Until** convergence

### 4. Experiments

In this section, we conduct extensive experiments on different datasets and models to validate the effectiveness of proposed data-free distillation method. Furthermore, we perform several ablation experiments to explore the influence of different components on data-free distillation performance.

#### 4.1 Datasets and Models

We validate the proposed distillation method on four datasets: MNIST, CIFAR10, CIFAR100, and Caltech101.

**MNIST.** MNIST [60] is a well-known image dataset of handwritten digits, which is composed of $28 \times 28$ pixels gray level images. It is very simple and only contains 10 classes (0 to 9) with 60,000 training images and 10,000 testing images. These images have been normalized and
located in the center of images. We use LeNet-5 [52] as teacher network and use a LeNet-5-Half [29] as student network.

**CIFAR10 and CIFAR100.** CIFAR10 and CIFAR100 [53] are slightly more complex image datasets. Both of them contain 50,000 training samples and 10,000 testing samples. CIFAR10 consist of $32 \times 32$ pixels color images with 10 categories, CIFAR100 have same image size and contains 100 categories. We choose ResNet-34 [58] as teacher model, and ResNet-18 as student model.

**Caltech101.** Caltech101 dataset [54] consists of 101 categories. Each category contains 40 to 800 images, and most categories have about 50 images. In training process, we split the samples into two parts, 80% images as training data, and 20% images as testing data. Also, we resize and center crop the images to $128 \times 128$ pixels during training. To generate larger images, we adopt a generator which stronger than that used on CIFAR and MNIST. Same as CIFAR datasets, we still use ResNet-34 network as teacher model, and ResNet-18 as student model.

### 4.2 Experimental Details

We implement all networks and distillation methods in PyTorch, and not use any data augmentation technique for making fair comparison. For all datasets, we adopt SGD with momentum 0.9 and weight decay $5 \times 10^{-4}$ to update student network and use Adam to optimize the generator. Moreover, we utilize the deep convolutional generators following [30] and make some adjustment to fit our method.

**Warm-up training strategy**

For reducing computational cost and training time, we proposed a simple training strategy, that is the warm-up training strategy. Different from warm-up which commonly used on learning rate adjustment, we propose a warm-up training strategy for saving computational cost. It is a tuning technique that can help us verify the effectiveness of new method and adjust hyper-parameters with minimal time consumption. Unlike the automatic hyper-parameter tuning techniques, our training strategy is a manual tuning approach. To be specific, if the model requires 200 training epochs and twice learning rate adjustment, we can train it 50 epochs and change learning rate once at 40th epoch. After comparing the results with different setting on warm-up training, we can judge model’s effectiveness and adjust the hyper-parameters with minimal computational cost. In this process, we also can clearly observe the influence of each component or hyper-parameter change. Then we can tune the hyper-parameters according to human prior knowledge. In order to further reduce computational cost, we can estimate whether current adjustment is effective according to the variation trend of training loss and testing accuracy. If the performance with current hyper-parameters is much worse than that in other settings, we could interrupt current training process in advance. When performance changes suddenly, we can decide whether to interrupt or continue training process according to our experience. All the actions mentioned above can greatly reduce training time and computational cost.

After accomplishing warm-up training with different hyper-parameters settings, we will select 2-4 groups better settings from them and conduct complete training with these settings. Then we select the settings with best result as final hyper-parameters. Although the final hyper-parameters may be not globally optimal, it is a balance of network performance and computational cost. It is worth noting that optimal settings obtained from warm-up training may be not the final best settings. We believe that although the optimal hyper-parameters obtained from warm-up training could not achieve best results, they can make models converge faster. In fact, if target task does not require a very high precision, we can use these settings to obtain suboptimal but faster convergence models.

**Evaluation Metric**

In classification tasks, classification accuracy is often used to evaluate different methods. For comparing different distillation methods, we usually use accuracy gap between teacher and student models to appraise the effectiveness of different distillation techniques. However, teacher models used in different distillation works are different and have different accuracy. It is difficult to compare the effectiveness of different distillation methods. To this end, we propose an additional evaluation metric to evaluate different distillation approaches. We define it as relative accuracy:

$$A_{rel} = \frac{A_T}{A_S} \times 100\%$$

(17)

where $A_T$ and $A_S$ are the accuracy of teacher and student networks. With relative accuracy, we can directly compare different distillation methods, thus avoiding the impact of using different teacher networks.

### 4.3 Experimental Results

**Experiments on MNIST**

We first implement proposed method on MNIST which is compose of $28 \times 28$ pixels. In training process, we resize images to $32 \times 32$ pixels and use batch size of 512. The initial learning rates are 0.01 and 0.001 for student and generator, respectively. For the experiments on MNIST, we train networks 60 epochs and adjust learning rates once at 50th epoch. In each epoch, we iterate the training process 50 times and set $k$ as 5. It should be noted that LeNet-5 architecture not contain batch-norm layers, so we discard BNS loss on MNIST dataset. In addition, we found student network will quickly converge to a high accuracy when the batch size is 512, and the generator could produce meaningful images after several epochs training. To this end, we should pay more attention to training epoch and avoid the models over-fitting on simple task. It is worth noting that, data-free generator tends to produces semantic images due to the lack of supervision of real images, while conventional GAN will produce natural images.

Table 1 reports the results of different data-free distillation method on MNIST dataset. With the absence
of real training data, DAFL [29], DFAD [30] and DFKD [55] obtained 99.28%, 99.32% and 99.53% relative accuracy on MNIST, respectively. After completing adversarial training, student network in our method achieves 98.62% classification accuracy and 99.65% relative accuracy while teacher network has 98.97% classification accuracy. Our method achieves a little but non-negligible gain when the accuracy is very close to upper bound. Excellent results on MINIST demonstrate the effectiveness of proposed method.

Table 1. Classification accuracy and relative accuracy of different methods on MNIST dataset. Teacher models have different accuracy in different methods.

| Method   | Teacher Acc (%) | Student Acc (%) | Relative Acc (%) |
|----------|----------------|----------------|-----------------|
| DAFL [29]| 98.91          | 98.20          | 99.28           |
| DFAD [30]| 98.97          | 98.30          | 99.32           |
| DFKD [55]| 98.97          | 98.45          | 99.53           |
| Ours     | 98.97          | 98.62          | 99.65           |

Experiments on CIFAR

CIFAR10 and CIFAR100 datasets are composed of 32 × 32 pixel images and have 10 and 100 categories, respectively. For CIFAR datasets, we set initial learning rate of student network and generator to 0.1 and 0.001. In training process, we use training epoch of 250, and decay learning rates twice. Also, we train student and generator models 100 times in each epoch, and use the batch size of 256. Under this setting, student network can see 256×100×5 (K=5) synthetic images in each epoch. It is even more than the images in original CIFAR datasets. Under the adversarial distillation framework, student model could sufficiently explore data space and be fully trained. Since CIFAR datasets and ResNet18 network are more complex than MNIST and LeNet-5 model, complete training process will take a lot of time. To this end, we adopt warm-up training strategy to tune hyper-parameters and train models. To be specific, we use 70 epochs and 50 iterations in each epoch for warm-up training while complete training requires 250 epochs and 100 iterations. In addition, we decay learning rates once at 50th epoch. It should be noted that, although training epochs and learning rates in CIFAR datasets are identical, we still need to adjust hyper-parameters in two datasets according to experimental results.

For CIFAR datasets, we select three better settings of hyper-parameters after warm-up training and then perform complete training. Table 2 summarizes experimental results of different works on CIFAR10. On CIFAR10, LS-GDFD [31] proposed by Google Research achieved best results of 99.97% relative accuracy and 95.02% student accuracy. Their results were only 0.03% less than teacher accuracy, which was amazing. According to their paper, however, LS-GDFD use 32768 batch size and 60K epochs on CIFAR datasets, while we use batch size of 256 due to the limitations of computational resources. Even so, we obtain 95.19% student accuracy and 99.63% relative accuracy on CIFAR10 which much better than previous works. For CIFAR100, we achieve 76.80% student accuracy and 99.07% relative accuracy which even outperforms the experimental results of LS-GDFD. This suggests that our method is not only applicable for simple datasets and networks, but also for complex datasets and networks. It should be noted that, LS-GDFD proposed train one generator for each category images to avoid mode collapse and improve student accuracy. Their method is useful but requires heavy computational resources. For fair comparison, we only compare experimental results with their results on single generator. Figure 2 shows the synthetic images on CIFAR datasets.

![Synthetic images on CIFAR datasets](image)

Figure 2. Synthetic images on CIFAR10 (top) and CIFAR100 (bottom), and each row have same category. Left: Real images sampled from real datasets. Right: Images generated by the conditional generator. Notably, since no real data is provided, the generator tend to produces semantic images rather than natural images.

Experiments on Caltech101

MNIST and CIFAR datasets are composed of low-resolution images, we also extend experiments to other high-resolution datasets to further validate the effectiveness of proposed method. Caltech101 contains 101 categories and each image is larger than 128×128, so we resize images to 128×128. In training process, we set batch size and training epoch to 128 and 300, respectively. We set initial learning rates of student model and generator to 0.05 and 0.001. Same as the experiments on CIFAR datasets, we employ warm-up training strategy on Caltech101. In warm-up training process, we train models 70 epochs to search optimal hyper-parameters and explore effects of each component. For generating larger images, we adjust the generator in DCGAN [59] to fit our method.
Table 2. Experimental results of different methods on CIFAR. We achieve comparable or even better results on CIFAR10 and state-of-the-art results on CIFAR100. It demonstrates the superiority of our method.

| Method      | CIFAR10 Teacher Acc (%) | Student Acc (%) | Relative Acc (%) | CIFAR100 Teacher Acc (%) | Student Acc (%) | Relative Acc (%) |
|-------------|-------------------------|-----------------|------------------|--------------------------|-----------------|------------------|
| DAFL        | 95.58                   | 92.22           | 96.48            | 77.84                    | 74.47           | 95.67            |
| DFAD        | 95.54                   | 93.3            | 97.65            | 77.50                    | 67.7            | 87.35            |
| LS-GDFD [31] | 95.05                   | **95.02**       | **99.97**        | 77.26                    | 74.45           | 98.91            |
| CMI [56]    | 95.70                   | 94.84           | 99.10            | 78.05                    | 77.00           | 98.71            |
| DDAD [57]   | 95.54                   | 94.81           | 99.23            | 77.50                    | 75.04           | 96.83            |
| DFKD [55]   | 95.32                   | 92.84           | 97.40            | 77.28                    | 74.45           | 96.34            |
| Ours        | 95.54                   | **95.19**       | **99.63**        | 77.52                    | **76.80**       | **99.07**        |

method and produce training images.

Table 3 reports the experimental results on Caltech101. With same teacher accuracy, DFAD and DDAD obtained 73.5% and 75.01% student accuracy. Compare with existing methods, our approach achieves the best student accuracy of 76.46% and highest relative accuracy of 99.84%. It demonstrates that our method is not only adapted to low-resolution images but also can be extended to other tasks on larger images. Furthermore, Figure 3 shows the gradient-weighted class activation heatmap of teacher and student model on images, where the teacher model is trained on real training data and the student network is trained with proposed data-free distillation framework. The visualization results show that student network can well extract local and global features of the image, which proves that student network have well learned the teacher's attention ability. Also, it demonstrates the effectiveness of feature-based distillation methods.

Table 3. Student accuracy and relative accuracy on Caltech101. We obtain the state-of-the-art results.

| Method | CIFAR100 Teacher Acc (%) | Student Acc (%) | Relative Acc (%) |
|--------|--------------------------|-----------------|------------------|
| DFAD   | 76.60                    | 73.5            | 95.95            |
| DDAD   | 76.60                    | 75.01           | 97.92            |
| Ours   | 76.58                    | **76.46**       | **99.84**        |

4.4 Ablation Experiments

In above sections, we have conducted extensive experiments on different datasets, and the experimental results demonstrate that our method can be applied to different data-free distillation tasks. However, our method different data-free distillation tasks. However, our method contains many different components, and each component has different role. Besides the loss functions that proposed in previous works, we introduce three novel loss functions for proposed data-free distillation framework, that is, Ground Truth loss (GT), Classes Matching loss (CM) and Attention Transfer loss (AT). To explore the role of each function, we perform ablation experiments on CIFAR100. In ablation studies, we follow the experimental settings on section 4.3. We perform different combinations of these loss functions to investigate the role each part plays. In proposed method, GT loss makes student network subject to the supervision of preset labels, and it only works when the category of synthetic images is controlled by CM loss. In other words, GT loss cannot independent of CM loss. In this case, we set several different combinations of these...
functions to verify the effectiveness of them. Table 4 reports the results of various design components.

In first ablation experiment, we introduce attention transfer to distillation framework. The student accuracy without any novel loss is 74.81%, and it will be improved to 76.34% with the AT loss. The great gain demonstrate that attention transfer can greatly improve the performance of student network. Actually, a pre-trained teacher model will focus on the target area of input images and capture useful information. In this situation, student network can learn the knowledge from teacher and achieve better performance through attention transfer. Besides the attention transfer, there are many useful feature-based distillation method, and the challenges remain. Since the ablation study have proved the effectiveness of feature-based distillation method, we will explore other effective feature-based distillation methods and improve the data-free distillation task. First, the representation of teacher’s knowledge. Feature map includes rich and varied information, and it should be converted into a simple form to make student network can learn easier. However, the process of transformation inevitably leads to the loss of information. To this end, we should explore more effective representations so that student network can easily learn and avoid information loss. Second, the selection of distillation position. Most studies manually select distillation features according to experience. To tackle this problem, we hope to design a reasonable adaptive distillation position selection technique to select feature maps that contain more information.

In other ablation experiments, we found CM loss also significantly improve student accuracy. We believe this is because the generator is subjected to additional supervision, and tighter constraint make generator converge faster. Furthermore, if we use AT loss together with CM loss, student model will obtain higher accuracy of 76.71%. Also, it has best performance of 76.80% when using all of these loss functions. We found that although GT loss does not significantly improve student accuracy, it can greatly accelerate the convergence of model. It is also worth noting that, the generator will produce meaningless images in early stages of training, so we use a small GT ratio and make student network subject to strong constraint of teacher model. As training proceeds, the synthetic images will become more meaningful, and we gradually increase the ratio of GT loss. The ablation experiments demonstrate that each proposed loss function is meaningful. Under the data-free distillation framework, generator could craft images according to specified category, student network can effectively learn the knowledge of teacher model and achieve better performance.

5. Conclusion

In this work, we propose a conditional generative data-free knowledge distillation method to train an efficient portable student network. This method introduces preset labels as auxiliary information to train the conditional generator. Then we force student model to mimic teacher’s attention maps and improve its performance. Without any real images, we successfully train a portable and efficient student network and achieve state-of-the-art results on several datasets.

Although there are several data-free distillation methods, the challenges remain. In future, we will do some works on the effective representation of teacher knowledge and the selection of distillation position. If there is a large gap between the capability of teacher and student model, how to optimize the student network? Moreover, training a generator from scratch is also computationally expensive, is there more efficient approach to improve this framework? We believe that these questions are the challenges and potentials for data-free distillation and even for whole distillation field, which need to be further explored.

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