Complementary Calibration: Boosting General Continual Learning With Collaborative Distillation and Self-Supervision

Zhong Ji®, Senior Member, IEEE, Jin Li®, Qiang Wang®, and Zhongfei Zhang®, Fellow, IEEE

Abstract—General Continual Learning (GCL) aims at learning from non-independent and identically distributed stream data without catastrophic forgetting of the old tasks that don’t rely on task boundaries during both training and testing stages. We reveal that the relation and feature deviations are crucial problems for catastrophic forgetting, in which relation deviation refers to the deficiency of the relationship among all classes in knowledge distillation, and feature deviation refers to indiscriminative feature representations. To this end, we propose a Complementary Calibration (CoCa) framework by mining the complementary model’s outputs and features to alleviate the two deviations in the process of GCL. Specifically, we propose a new collaborative distillation approach for addressing the relation deviation. It distills model’s outputs by utilizing ensemble dark knowledge of new model’s outputs and reserved outputs, which maintains the performance of old tasks as well as balancing the relationship among all classes. Furthermore, we explore a collaborative self-supervision idea to leverage pretext tasks and supervised contrastive learning for addressing the feature deviation problem by learning complete and discriminative features for all classes. Extensive experiments on six popular datasets show that our CoCa framework achieves superior performance against state-of-the-art methods. Code is available at https://github.com/lijincm/CoCa.

Index Terms—General continual learning, complementary calibration, knowledge distillation, self-supervised learning, supervised contrastive learning.

I. INTRODUCTION

HUMAN beings have the capability to continuously acquire, adjust and transfer knowledge, which is just what we desire agents to have. Continual learning [1], [2], also called incremental learning or lifelong learning, focuses on the problem of learning from a data stream in non-stationary data distributions. These data come from different tasks, in which the input domains are constantly changing. In this situation, we hope to exploit the acquired knowledge to solve the old and new tasks. Continual learning has a wide range of related applications in the real world, such as object detection [3], product search [4] and 3D object classification [5].

The main challenge in continual learning is catastrophic forgetting [6], that is, when a deep neural network is trained on a new task, the performance on old tasks usually drops significantly. To prevent the catastrophic forgetting, we hope that the model is capable to integrate new and existing knowledge from new data (plasticity) on the one hand, and prevent the significant interference of new input on existing knowledge (stability) on the other hand. These two conflicting demands constitute the stability-plasticity dilemma [1].

Early studies of continual learning primarily focused on the Task Incremental Learning (Task-IL) scenario [7], [8], [9], in which the difficulty is greatly reduced by employing task boundaries during testing stage. Recently, lots of studies consider a more challenging setting, i.e., Class Incremental Learning (Class-IL) [10], [11], [12], in which task boundaries are unavailable when testing stage. However, existing methods for both Task-IL and Class-IL rely on task boundaries at the training stage, which are not in line with the practical requirement. In this paper, we consider a more complex and practical setting: General Continual Learning (GCL) [2], [13], whose task boundaries are not available during both training and testing stages. Therefore, most of the existing continual learning methods that utilize task boundaries at the training stage cannot be directly applied to GCL.

Recently, Buzzega et al. [13] proposed a simple and strong GCL baseline named Dark Experience Replay (DER). They balanced the stability-plasticity dilemma by knowledge distillation. Concretely, they took the old model as the teacher and reserved the old model’s outputs to constrain the new model’s outputs of the old samples. However, new samples are unseen to the old model, which lead to inaccurate old model’s outputs. As shown in Fig. 1, the outputs of an old model lack the relationship between the old and new classes. In addition, when a new task consists of new samples of the old classes, the relationship among the classes in the old model may be incomplete. We refer to the deficiency of the relationship among all classes in knowledge distillation as relation deviation, which makes interference in balancing the relationship of the old and new classes.

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Zhongfei Zhang is with the Department of Computer Science, Binghamton University State University of New York, Binghamton, NY 13902 USA (e-mail: zzh@binghamton.edu).

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exploiting pretext tasks and supervised contrastive learning, in which pretext tasks enable the feature extractor to learn complete features, while supervised contrastive learning maintains the meaningful transformation of pretext tasks and learns discriminative features between the new and old classes. Pretext tasks and supervised contrastive learning complement each other, ensuring the feature representations to be complete and discriminative for all classes in GCL. The proposed framework is shown in Fig. 3.

The main highlights are summarized below:

1. We reveal that relation and feature deviations are crucial problems for catastrophic forgetting in GCL, and propose a novel Complementary Calibration (CoCa) framework for GCL to alleviate these two deviations by exploring the complementary information of model’s outputs and features.

2. We ensemble dark knowledge to alleviate the relation deviation, keeping the performance of the old tasks and balancing the relationship of inter-class by collaborative distillation.

3. We leverage a collaborative self-supervised network by exploiting pretext tasks and supervised contrastive learning, which enables feature extractor to learn complete and discriminative features for all classes in GCL.

4. Extensive experiments on six popular datasets, namely sequential CIFAR-10, sequential CIFAR-100, sequential Tiny ImageNet, MNIST-360, UG-CIFAR-100 and LG-CIFAR-100, show that our CoCa framework outperforms the state-of-the-art methods.

II. RELATED WORK

A. Continual Learning

Early studies focus on Task Incremental Learning (Task-IL) [2], the simplest continual learning scenario, in which the task boundaries are available during both training and testing stages. Such approaches can be roughly categorized into three types: rehearsal-based methods, regularization-based methods and structure-based methods. Rehearsal-based methods [14], [15] replay reserved samples from old tasks while learning a new task to mitigate catastrophic forgetting. Regularization-based methods [8], [9], [16] constrain the parameters of each part of the model to protect the previously learned knowledge. Structure-based methods [17], [18], [19] alleviate catastrophic forgetting by modifying the underlying architecture of the network.

Due to the rigid restriction of Task-IL, recent studies pay more attention on Class Incremental Learning (Class-IL) [10], [20], which prohibits access to the task boundaries during testing stage. Different from Task-IL, Class-IL needs to distinguish all seen classes when testing stage. Many studies [10], [21], [22] have revealed that Class-IL models are easily biased into new classes, thus existing efforts usually aim at alleviating this problem by deviation amendment from features or classifier. Methods from the feature aspect mainly consider how to learn transferable and complete features, such as class augmentation [23], mutual information maximization [24], gradient-based meta learning [25]. The other methods from the classifier aspect consider how to reduce the classifier bias caused by the imbalance between the new and old tasks, such as semantic augmentation [23], class statistics [26] and weight aligning [22].

Although great progress has been achieved, most Task-IL and Class-IL approaches depend on task boundaries in the
training stage. Actually, task boundaries are blurry in practical scenarios due to the fact that stream data usually have not clear task divisions. Thus, recent studies set out to explore General Continual Learning (GCL) [2], [13], whose differences from the Task-IL and Class-IL settings are mainly in two aspects: (i) Task boundaries are not necessary during both training and testing stages; (ii) Memory size is limited even facing infinite stream data. Therefore, it is a quite challenging setting.

Some efforts towards GCL are from the aspect of the sample strategy. David and Akansel [27] employed the reservoir sample strategy so that the probability of all samples can be selected is equal. Buzzega et al. [28] further introduced a loss-aware reservoir sampling (LARS) to select important samples. Quang et al. [29] utilized unsupervised contrastive learning to learn a general representation. Rahaf et al. [30] proposed a greedy selection method named Gradient based Sample Selection (GSS), which aims at improving the diversity of samples. Afterward, some methods concentrate on mixed methods. Rao et al. [31] proposed an unsupervised continual learning approach called CURL with model expansion and generative replay to maintain the performance of old tasks. On the basis of CURL, Lee et al. [32] proposed Continual Neural Dirichlet Process Mixture (CN-DPM), which utilizes the Bayesian nonparametric framework to enlarge the number of experts. Buzzega et al. [13] proposed Dark Experience Relay++ (DER++) with the combination of regularization and rehearsal-based methods, which employs experience replay and knowledge distillation to promote the new model’s outputs consistency with the original outputs. Our CoCa framework also combines knowledge distillation with rehearsal, the key difference is that we explore collaborative distillation to balance the relationship among all classes by utilizing new model’s outputs.

B. Knowledge Distillation

Knowledge distillation [33] refers to the approach that the training process of a student model is supported under the supervision of a teacher model with dark knowledge (soft targets). Dark knowledge contains richer similarity relationship among all classes. In addition, the student model could distill knowledge by itself, which is called self-distillation [34]. Knowledge distillation is widely applied in continual learning to address the catastrophic forgetting problem. LWF [35] is the earliest work to explore it in continual learning, which aims at leveraging new samples of the old model’s outputs to constrain the new model’s outputs. Afterward, FDR [36] stores samples as well as the dark knowledge of the old model, and constrains the \( \ell_2 \) norm of the difference between the new model’s outputs and dark knowledge. Unlike the label distillation, LUCIR [10] directly limits the normalized features extracted by the new model as consistent as those by the old model, while PODNet [11] constrains the evolution of each layer’s output. Further, GeoDL [37] distills the geodesic path between the old and new models’ features, while DDE [12] introduces causal inference to distill the casual effect between the old and new data. Different from them, our proposed collaborative distillation explores ensemble dark knowledge from old and new models, which contains more informative similarity relationships than that from a single model.

C. Self-Supervised Learning

Self-Supervised Learning (SSL) [38] refers to learning representations with large amounts of data without manual labels, which explores input samples’ inherent co-occurrence relationships as supervision. A typical type of SSL is pretext tasks, which generally leverage the spatial structure or sequential relationships of input images, such as pretext-invariant representations [39] and geometric transformation [40]. Another
type is unsupervised contrastive learning [41], [42], which utilizes the contrastive loss to pull multiple views of an image closer and pushes those apart from other samples in an embedding space. SSL is widely applied in many fields, including few-shot learning [43], imbalance learning [44] and continual learning [45]. Zhu et al. [45] utilized pretext task based self-supervised label augmentation [46] to learn more transferable features. Khosla et al. [47] extended unsupervised contrastive learning to the supervised setting by employing images from the same class as positive samples. Positive samples are pulled closer and the other samples are pushed away in an embedding space. Mai et al. [48] proposed Supervised Contrastive Replay (SCR), leveraging supervised contrastive learning and nearest-class-mean classifier to mitigate catastrophic forgetting. Cha et al. [49] further proposed Contrastive Continual Learning (CO^2L), introducing self-supervised instance-wise relation distillation and asymmetric supervised contrastive learning to learn and preserve representations.

One closest to our method is CO^2L [49] which also combines the self-supervised learning and the supervised contrastive learning for continual learning. However, CO^2L conducts the self-supervised learning by employing an instance-wise relation distillation between the previous and current models rather than utilizing the pretext task. Moreover, the self-supervised instance-wise relation distillation relies on the task boundaries to appoint the previous model as the teacher model, which is not in line with GCL setting. Other similar works are PASS [45] and SCR [48], which adopt single self-supervised learning or supervised contrastive learning for continual learning, respectively. Different from our CoCa that requires no task boundaries, PASS depends on the task boundaries to appoint the teacher model, and SCR depends on the task boundaries to update the memory buffer.

### III. METHODOLOGY

In this work, we focus on GCL in image classification. Formally, given stream data characterized by tasks \( D_1, D_2, \ldots, D_T \), each task \( D_t = \{(x_{t,i}, y_{t,i})\}_{i=1}^{N_t} \) consists of \( N_t \) images \( x \in \mathcal{X} \) and labels \( y \in \mathcal{Y} \) corresponding to \( x \). The task boundaries are unavailable during both training and testing stages. To alleviate the catastrophic forgetting, following [13], [28], and [50], we employ memory buffer \( \mathcal{M} = \{(\hat{x}_i, \hat{y}_i)\}_{i=1}^{B} \) to store limited samples \((x, y)\) that were not augmented and corresponding model’s outputs \( \hat{o} \), where \( B \) represents buffer size.

As shown in Fig. 3, our proposed CoCa framework consists of three parts: an Experience Replay Module, a Relation Calibration Module and a Feature Calibration Module. In what follows, we first introduce Experience Replay Module and analyze the relation deviation among classes in existing knowledge distillation methods. Then in Relation Calibration Module, we elaborate on how collaborative knowledge distillation mitigates the relation deviation. Finally, the Feature Calibration Module leverages collaborative self-supervision to alleviate the feature deviation, which is composed of pretext tasks based on geometric transformations and supervised contrastive learning to learn complete and discriminative features respectively. Interestingly, the alleviation process for relation and feature deviations are mutually complementary.

#### A. Experience Replay Module

Our feature extractor \( f_{\Theta} \) for GCL is a neural network, parameterized with parameters \( \Theta \). The role of \( f_{\Theta} \) is to extract feature representations of all tasks. Meanwhile, a classifier \( f_{\hat{\Theta}} \) needs to be trained to project the learned feature representations into the label space. The ideal goal is to minimize the following formula:

\[
\min_{\Theta, \hat{\Theta}} \sum_{t=1}^{T} \mathbb{E}_{(x, y) \sim D_t} \mathcal{L}_{CE} \left( \sigma \left( f_{\Theta, \hat{\Theta}}(Aug(x)) \right), y \right),
\]

(1)

where \( Aug(\cdot) \) refers to data augmentation function, \( \sigma(\cdot) \) is the softmax function and \( \mathcal{L}_{CE} \) is the cross-entropy loss. Since it is unavailable to get all samples from old tasks, Experience Replay Module stores a subset of previous training set and employs them to jointly optimize models. This is equivalent to correctly classifying new tasks given limited memory \( \mathcal{M} \) from old tasks. Therefore, Eq. 1 is substituted by the following loss terms:

\[
\mathcal{L}_{ER} = \mathbb{E}_{(x, y) \sim D_t} \mathcal{L}_{CE} \left( \sigma \left( f_{\Theta, \hat{\Theta}}(Aug(x)) \right), y \right)
+ \mathbb{E}_{(x, y) \sim \mathcal{M}} \mathcal{L}_{CE} \left( \sigma \left( f_{\Theta, \hat{\Theta}}(Aug(x)) \right), y \right).
\]

(2)

Experience Replay Module is widely applied in image classification. For example, Buzzega et al. [13] proposed a strong baseline dubbed DER that employs experience replay and knowledge distillation to maintain the performance of old tasks on GCL setting. In particular, it constrains the new model’s outputs to be as consistent as possible with the old model. Formally, the loss is written as:

\[
\mathcal{L}_{KD} = \mathbb{E}_{(x, \hat{o}) \sim \mathcal{M}} \| f_{\Theta, \hat{\Theta}}(Aug(x)) - \hat{o} \|_2^2,
\]

(3)

where \( \hat{o} \) are the model’s outputs sampled from old models and the \( \| \cdot \|_2 \) operator refers to the \( \ell_2 \) norm.

However, when training the new model in GCL, \( \hat{o} \) is deficient to express the relationship among all classes. We refer to this deficiency as relation deviation.

#### B. Relation Calibration Module

As mentioned above, the relation deviation in GCL is caused by forcing the outputs of new model to keep consistent with the old model’s outputs, which lack whole inter-class relationships compared with the outputs of new model. Meanwhile, when the model is trained on a new task, its performance on old tasks usually drops significantly, indicating inaccurate outputs of the new model on old tasks. Fortunately, this deficient inter-class relationships exist in the new model’s outputs and this inaccuracy can be compensated by the old model’s outputs. Therefore, we naturally aim to explore complementary properties of the two outputs by forcing the new model’s outputs to be consistent with the ensemble outputs of old and new models.

Specifically, we propose a collaborative distillation loss \( \mathcal{L}_{CKD} \) to keep the new model’s outputs \( o \) consistent with the
ensemble outputs \( o^*(o, \hat{o}) \) obtained by Relation Calibration Module. It utilizes the features similarity matrix, the new model’s outputs \( o \) of and the reserved outputs \( \hat{o} \) of the old model to obtain ensemble outputs \( o^*(o, \hat{o}) \). Hence, the learning objective for collaborative knowledge distillation is:

\[
\mathcal{L}_{CKD} = \mathbb{E}_{(x, \hat{x}) \sim \mathcal{M} \mid (o - o^*(o, \hat{o}))^2. \tag{4}
\]

Noticeably, we cannot directly combine \( o \) and \( \hat{o} \) linearly. Otherwise, if the ensemble outputs \( o^*(o, \hat{o}) \) are composed by \( o^*(o, \hat{o}) = \gamma o + (1 - \gamma) \hat{o} \), where \( \gamma \) is a positive trade-off hyper-parameter to balance \( o \) and \( \hat{o} \), \( \mathcal{L}_{CKD} \) and \( \mathcal{L}_{KDL} \) will be linearly correlated:

\[
\begin{align*}
\mathcal{L}_{CKD} &= \mathbb{E}_{(x, \hat{x}) \sim \mathcal{M} \mid (o - (\gamma o + (1 - \gamma) \hat{o}))^2 \tag{5} \\
&= (1 - \gamma)^2 \mathcal{L}_{KDL}.
\end{align*}
\]

Meanwhile, the new model’s outputs may inaccurate. Therefore, we adopt the similarity of the features in the same batch to propagate the new model’s outputs \( o \) and fuse the old model’s outputs \( \hat{o} \). In this way, the ensemble outputs \( o^*(o, \hat{o}) \) are carried out to obtain complete inter-class relationships, which are calculated by the following three steps. Firstly, we calculate the normalized samples’ similarity \( \hat{S}(i, j) \) in the same batch. For each pair of samples \( (x_i, x_j) \), the normalized feature embeddings obtained by the feature extractor \( f_\theta \) is \( (\hat{z}_i, \hat{z}_j) \), the normalized samples’ similarity matrix \( \hat{S} \in \mathbb{R}^{N \times N} \) is calculated by:

\[
\hat{S}(i, j) = \frac{\exp(S(i, j))}{\sum_{k \neq i} \exp(S(i, k))}, \tag{6}
\]

where the similarity function \( S(i, j) \) is defined as:

\[
S(i, j) = \left\{ \begin{array}{ll}
\hat{z}_i^T \hat{z}_j & (i \neq j) \\
0 & (i = j)
\end{array} \right.. \tag{7}
\]

Secondly, we conduct label propagation by \( o \) and normalized similarity matrix \( \hat{S} \) described in [51] as:

\[
Q_t = \omega \hat{S} Q_{t-1} + (1 - \omega) (t \geq 0), \tag{8}
\]

where \( \omega \) is a weighting factor in range \([0, 1]\) and \( Q_0 = o \). The label propagation is conducted many times for obtaining more accurate outputs:

\[
Q_\infty = \lim_{t \to \infty} \left( \omega \hat{S} \right)^t o + (1 - \omega) \sum_{t=1}^{t-1} \left( \omega \hat{S} \right)^i o. \tag{9}
\]

Since \( \omega \) and the eigenvalues of \( \hat{S} \) are both in range \([0, 1]\), we obtain an approximate formulation for \( Q_\infty \) as:

\[
Q_\infty = (1 - \omega) \left( I - \omega \hat{S} \right)^{-1} o, \tag{10}
\]

where \( I \) is an identity matrix.

Finally, the ensemble outputs \( o^*(o, \hat{o}) \) consist of the old model’s outputs \( \hat{o} \) and the modified outputs \( Q_\infty \), which is written as:

\[
o^*(o, \hat{o}) = \gamma (1 - \omega) \left( I - \omega \hat{S} \right)^{-1} o + (1 - \gamma) \hat{o}. \tag{11}
\]

Since the modified new model’s outputs \( Q_\infty \) ensembles the similarity information of other samples, \( o^*(o, \hat{o}) \) contains more informative similarity relationships than \( \hat{o} \) from old model. In this way, we alleviate the relation deviation among all classes of the old model’s outputs. Even if the matrix inversion operation takes \( O(n^3) \) time complexity, the computational complexity is trivial when the batch size \( n \) is limited.

### C. Feature Calibration Module

Besides relation deviation, feature deviation is another key challenge, which is caused by the indiscriminative feature representations. To address this challenge, we develop a Feature Calibration Module, which consists of pretext tasks and supervised contrastive learning. In detail, we first design self-supervised pretext tasks as auxiliary supervision, enabling the feature extractor to learn complete features. Then, we utilize supervised contrastive learning to learn discriminative features between the new and old classes.

As the samples of the old tasks are unavailable in GCL, the feature extractor tends to extract the discriminative features for the new incoming task. This tendency results in incomplete feature representations, which generally cannot well distinguish the old tasks from the new ones. To calibrate incomplete feature representations, we exploit self-supervised learning based on geometric transformations pretext tasks to enable the feature extractor to exact complete features, which represents the rich spatial or sequential relationships of the samples. In particular, we apply pretext tasks loss \( \mathcal{L}_{PT} \) to distinguish what geometric transformation has been made to the original images. Among them, a multi-layers perception \( f_\psi \) is applied as the auxiliary classifier to project the feature exacted by \( f_\psi \) into the label space. Accordingly, the pretext tasks loss \( \mathcal{L}_{PT} \) of geometric transformation tasks are designed as:

\[
\mathcal{L}_{PT} = \mathcal{L}_{CE}(\sigma(f_\theta, \phi(x^p, y^p))), \tag{12}
\]

where the proxy label \( y^p \) consists of a series of geometric transformations, such as rotation and scaling, image \( x^p \) is produced by applying geometric transformations proxy label \( y^p \) to the original image \( x \).

To better learn discriminative features for all tasks, we further leverage supervised contrastive learning in CoCa framework. In detail, we introduce another MLP \( f_\phi \) with parameters \( \phi \), whose purpose is to map the feature to an embedding space where the supervised contrastive learning loss is applied. In the feature space, the distances from the same class are shortened and those of different classes are enlarged. Assuming the embedding \( z = \{f_\theta, \phi(Aug(x))\} \cup \{f_\phi, \phi(x^p)\} \), \{\( z^+ \)\} and \{\( z^- \)\} represent the set of all positive and negative samples distinct from each other in the multi-viewed batch respectively, the supervised contrastive learning loss function is written as:

\[
\begin{align*}
\mathcal{L}_{SCL} = \mathbb{E}_{x_i \sim A}[ & \sum_{z_j \sim |z^+_i|} \frac{S(z_i, z_j)}{\tau} \\
+ & \log(\sum_{z_j \sim |z^-_i|} \exp(S(z_i, z_j))) \\
+ & \sum_{z_k \sim |z^-_i|} \exp(S(z_i, z_k))], \tag{13}
\end{align*}
\]
where \((i, j, k)\) denotes the index, \(\tau\) is a scalar temperature parameter, and \(\sum_{z_i \sim \mathcal{G}(\tau)} \exp \left(\frac{c_{ij}}{\tau}\right)\) encourages samples from different classes to be as far away on the unit hypersphere as possible in Eq. 13. In this way, the features are evenly distributed on the unit hypersphere as far as possible. Supervised contrastive learning could well distinguish the old and new classes as it utilizes the label information.

Noticeably, pretext tasks and supervised contrastive learning are cooperative and complementary. Here, they not only cooperate together to obtain better feature representations to alleviate the feature deviation problem, but make up for their respective defects mutually. Concretely, on the one hand, the pretext tasks may be redundant, and even may produce interference. For example, it is difficult to distinguish the number 6 from the number 9 after 180° rotation. Thankfully, the supervised contrastive learning suppresses the redundancy of the pretext tasks by supervised information; on the other hand, when the samples of the old classes are missing due to the limited memory, the complete features learned by the pretext tasks assist the supervised contrastive learning to obtain discriminative features for all tasks. Therefore, the collaborative self-supervision loss \(\mathcal{L}_{CSS}\) of Feature Calibration Module becomes:

\[
\mathcal{L}_{CSS} = \mathcal{L}_{PT} + \mathcal{L}_{SCL}.
\] (14)

Feature Calibration Module explores existing samples and features to learn complete and discriminative features for both old and new tasks, these complementary sets of features alleviate catastrophic forgetting effectively.

D. The Overall Objective

Since our proposed CoCa framework consists of Experience Replay Module, Feature Calibration Module and Relation Calibration Module, the objective function of the whole training stage is as follows:

\[
\mathcal{L}_{CoCa} = \mathcal{L}_{ER} + \lambda_1 \mathcal{L}_{CKD} + \lambda_2 \mathcal{L}_{CSS},
\] (15)

where \(\lambda_1\) and \(\lambda_2\) are hyperparameters. At the test stage, the Feature Calibration Module and Relation Calibration Module are removed.

IV. EXPERIMENTS

A. Datasets

Two types of benchmarks are selected in our image classification experiments: sequential and smooth benchmarks.

Sequential benchmarks refer to the datasets that have clear task boundaries, such as sequential CIFAR-10, sequential CIFAR-100 and sequential Tiny ImageNet. CIFAR-10 [53] consists of 10 classes, each class has 6000 samples of 32 × 32 color images, including 5000 training samples and 1000 test samples. CIFAR-100 [53] is similar to CIFAR-10 except that the number of classes is 100. Each class has 600 images, which are divided into 500 for training and 100 for testing. Tiny ImageNet [54] is a subset of ImageNet [55], which contains 200 classes, and each class has 500 samples with 64 × 64 color images for training. We split the CIFAR-10, CIFAR-100 and Tiny ImageNet evenly into 5, 20 and 10 sequential tasks respectively, each of which includes 2, 5 and 20 classes, i.e., sequential CIFAR-10, sequential CIFAR-100 and sequential Tiny ImageNet.

Smooth benchmarks mean that the task boundaries are blurry and the same class repeatedly appears, which are specially designed for the GCL setting, such as MNIST-360 [13] and generalized CIFAR-100 [56], [57], [58]. In detail, MNIST-360 offers a sequence of MNIST numbers from 0 to 8 at increasing angles. It builds the batch by using samples belonging to two continuous subsequence classes at a time, such as (0, 1), (1, 2), . . . , (8, 0). Generalized CIFAR-100 has 20 tasks with 1,000 samples in each task, each task contains 1 to 50 classes. It contains two variations: Uniform Generalized CIFAR-100 (UG-CIFAR-100) and Longtail Generalized CIFAR-100 (LG-CIFAR-100). The difference between the two variations is that the number of samples of each class in each task of the former is equal, while that of the latter follows a longtail distribution.

B. Implementation Details

We employ a fully connected network with two hidden layers as the backbone for MNIST-360 dataset. For the other datasets, we employ ResNet-18 [59] as the backbone. And two fully connected networks with three hidden layers are employed as the projector and auxiliary classifier, respectively. The hyperparameters are selected via grid search by employing reserved samples of validation set from all task’s training sets. The number of epochs for datasets MNIST-360, sequential CIFAR-10, sequential CIFAR-100 and sequential Tiny ImageNet are 1, 50, 50 and 100, respectively. Following [13], we utilize Stochastic Gradient Descent (SGD) as optimizer and fix the batch size at 64 to ensure that the number of updates for all methods are the same. Concretely, each batch consists of 32 new samples and 32 replayed samples, and the latter are updated with reservoir sample strategy [60] at the end of each batch. Following [13], [28], and [50], we apply the data augmentation to the samples in the batch, including the random crops and horizontal flips. In Relation Calibration Module, we set both the weighting factor \(\omega\) and the trade-off hyper-parameter \(\gamma\) as 0.1. In Feature Calibration Module, the pretext tasks are composed of three types of geometric transformations, including rotation \([0°, 90°, 180°, 270°]\), scaling \([0.67, 1.0]\) and aspect ratio \([0.67, 1.33]\). Additionally, we only perform one geometric transformation for each sample to reduce the computational resource as well as execution time. Our approach is implemented with pytorch framework and trained on one NVIDIA GeForce RTX 3060 GPU.

C. Comparison With State-of-the-Art Methods

1) Competitors: Three group of competitors are selected. The first group is the GCL approaches, including (1) CN-DPM (continual neural dirichlet process mixture) [32]; (2) ER (experience replay with reservoir) [27]; (3) GSS (gradient sample selection) [30]; (4) DER (dark experience replay) [13]; (5) DER++ (dark experience replay++) [13]; (6) LARS
TABLE I
AVERAGE ACCURACY (%) ON SEQUENTIAL BENCHMARKS. “*” INDICATES THAT TASK BOUNDARIES ARE PROVIDED AT THE TRAINING STAGE, “†” REPRESENTS THAT THE ORIGINAL METHOD IS MODIFIED FOR GCL

| Method   | JOINT | sequential CIFAR-10 | sequential CIFAR-100 | sequential Tiny ImageNet |
|----------|-------|----------------------|-----------------------|--------------------------|
| SGD      | 92.20 | 69.55                | 59.99                 |                          |
| LIF* [35] | 19.61 | 4.26                 | 8.46                  |                          |
| oEWC* [16] | 19.49 | 3.49                 | 7.58                  |                          |
| SIF [9] | 19.48 | 4.60                 | 6.58                  |                          |
| CN-DPM [32] | 45.21 | 20.10                | -                     |                          |

| B        | 200  | 500  | 5120 | 200  | 500  | 5120 | 200  | 500  | 5120 |
|----------|------|------|------|------|------|------|------|------|------|
| iCaRL* [20] | 49.02 | 47.55 | 55.07 | 19.26 | 24.71 | 29.78 | 7.53 | 9.38 | 14.08 |
| FDR* [36] | 30.91 | 28.71 | 19.70 | 11.67 | 18.00 | 25.35 | 8.70 | 10.54 | 28.97 |
| HAL* [52] | 32.36 | 22.79 | 59.12 | 7.60  | 9.55  | 22.11 | 5.09 | 7.45  | 21.11 |
| A-GEM* [15] | 20.04 | 22.67 | 21.99 | 4.73  | 4.74  | 4.87  | 8.07 | 8.06  | 7.96  |
| GeoDL* [37] | 49.20 | 61.83 | 85.91 | 13.38 | 23.06 | 54.57 | 10.08 | 12.03 | 36.29 |
| CO2† [49] | 56.08 | 62.21 | 84.27 | 18.85 | 24.45 | 46.18 | 11.28 | 16.45 | 37.14 |
| ER [27] | 44.79 | 57.74 | 82.47 | 9.84  | 14.64 | 44.79 | 8.49  | 9.99  | 27.40 |
| GSS [30] | 39.07 | 49.73 | 67.27 | 6.35  | 7.44  | 9.71  | 8.55  | 9.63  | 14.16 |
| DER [13] | 61.93 | 70.51 | 83.81 | 15.22 | 24.11 | 44.80 | 11.87 | 17.75 | 36.73 |
| DER++ [13] | 64.88 | 72.70 | 85.24 | 18.66 | 28.70 | 51.20 | 10.96 | 19.38 | 39.02 |
| LARS [28] | 47.75 | 60.91 | 84.84 | 10.98 | 16.31 | 45.57 | 8.53  | 10.60 | 24.84 |
| DualNet [29] | 62.73 | 72.98 | 85.07 | 14.80 | 26.98 | 53.35 | 9.53  | 13.33 | 36.70 |

CoCa (Ours) | 66.25 | 76.27 | 89.52 | 21.20 | 32.88 | 58.38 | 12.78 | 20.33 | 39.79 |

TABLE II
AVERAGE ACCURACY (%) ON SMOOTH BENCHMARKS. “†” REPRESENTS THAT THE ORIGINAL METHOD IS MODIFIED FOR GCL

| Method   | MNIST-360 | UG-CIFAR-100 | LG-CIFAR-100 |
|----------|-----------|--------------|--------------|
| SGD      | 82.98     | 60.19        | 54.72        |
| JOINT   | 19.02     | 18.05        | 15.02        |

| B        | 200  | 500  | 5120 | 200  | 500  | 5120 | 200  | 500  | 5120 |
|----------|------|------|------|------|------|------|------|------|------|
| A-GEM† [15] | 28.34 | 28.13 | 29.21 | 18.13 | 18.87 | 19.91 | 15.53 | 16.69 | 17.49 |
| GeoDL† [37] | 34.17 | 70.64 | 78.98 | 25.78 | 33.53 | 37.22 | 23.88 | 32.00 | 36.73 |
| CO2† [49] | 39.30 | 69.10 | 76.83 | 24.67 | 26.12 | 33.69 | 22.97 | 24.04 | 31.02 |
| ER [27] | 49.27 | 65.04 | 75.18 | 24.20 | 27.65 | 32.89 | 21.56 | 24.79 | 32.25 |
| GSS [30] | 43.92 | 54.45 | 63.84 | 20.99 | 24.27 | 26.27 | 20.50 | 22.35 | 25.03 |
| DER [13] | 55.22 | 69.11 | 75.97 | 29.23 | 34.79 | 40.01 | 27.46 | 33.50 | 38.38 |
| DER++ [13] | 54.16 | 69.62 | 76.03 | 28.79 | 33.14 | 40.51 | 25.27 | 32.59 | 36.97 |
| LARS [28] | 47.68 | 66.74 | 74.34 | 21.24 | 26.25 | 29.47 | 22.17 | 24.41 | 30.05 |
| DualNet [29] | 57.06 | 72.23 | 79.15 | 20.11 | 25.31 | 28.28 | 19.28 | 23.78 | 27.60 |
| CoCa (Ours) | 67.02 | 76.49 | 81.82 | 30.52 | 35.21 | 41.18 | 29.68 | 33.79 | 39.35 |

(loss-aware reservoir sampling) [28] and (7) DualNet (Dual Networks) [29]. The second group is the continual learning approaches that can be applied for GCL by modifying the primitive methods, including (1) A-GEM (average gradient episode memory) [15]; (2) GeoDL (geodesic continual learning) and (3) CO2 (contrastive continual learning) [49]. The third group is the Class-IL and Task-IL approaches, in which task boundaries should be provided during training stage, including: (1) LWF (learning without forgetting) [35]; (2) oEWC (online elastic weight consolidation) [16]; (3) SI (synaptic intelligence) [9]; (4) iCaRL (incremental classifier and representation learning) [20]; (5) FDR (function distance regularization) [36]; and (6) HAL (hindsight anchor learning) [52]. In addition, we also report the performance bound, including: (1) JOINT represents that all data are available at any time, which is an upper bound; and (2) SGD means that no strategy is adopted to alleviate forgetting at the training time, which is the lower bound.

Following [2] and [13], we employ the average accuracy on all tasks as the evaluation criterion. To make a fair comparison, we apply the single-head setting during training stage and the pretrain model is unavailable in all methods. It should be emphasized that no task boundaries are provided for our proposed CoCa approach, even in comparison with those Class-IL and Task-IL approaches.

2) Results: Table I reports the results of the comparison on sequential benchmarks. It could be observed that our approach outperforms the competitors in all cases. Specifically, for sequential CIFAR-10 dataset, the proposed CoCa framework outperforms the state-of-the-art competitors at least in 1.37%. Furthermore, CoCa beats all methods on sequential CIFAR-100 dataset. For example, it surpasses the second-best method DER in 4.18% with 500 buffer capacity. As for the sequential Tiny ImageNet dataset, CoCa has a performance gain against the best competitor by 0.91%, 0.95% and 0.77% under 200, 500 and 5120 buffer capacity, respectively.

Since the smooth benchmarks have no task boundaries, many methods that rely on task boundaries are inadequate for it, such as LWF [35], oEWC [16], SI [9], iCaRL [20], FDR [36], and HAL [52]. Thus, their methods are unavailable on smooth benchmarks. As shown in Table II, we could observe that our CoCa framework achieves top performance across all the different buffer sizes on the three datasets. Take the MNIST-360 dataset for example, CoCa outperforms
the suboptimal method at least in 2.67%. It is quite impressive when the buffer size is limited, such as 200, with at least 7.72% gains against the other competitors. Moreover, we could observe that the performance on the UG-CIFAR-100 dataset performs better than the LG-CIFAR-100 dataset. This is mainly due to that the imbalance of classes exacerbates relation and feature deviations. These results indicate that collaborative distillation and self-supervision greatly alleviate catastrophic forgetting by mitigating deviation in the absence of task boundaries.

In addition, we also observe significant performance differences of CoCa on different datasets and different buffer sizes. Specifically, it can be observed that the performance on sequential CIFAR-10 dataset is higher than sequential Tiny ImageNet and sequential CIFAR-100 datasets. The reason lies in that it has quite fewer classes than the other datasets. For the performance differences among different buffer sizes for the same dataset, it is due to that the more replay samples are retained, the easier it is to alleviate the deviation. When the buffer size is large enough, it approximates the setting of joint training, i.e., the performance upper bound. As we can see, as the buffer size increases from 200 to 5120, the average accuracy improves by at least 23% on these datasets.

D. Ablation Study

1) The impact of each component: To evaluate the impact of different components in CoCa, we conduct ablation studies on sequential CIFAR-100 and MNIST-360 datasets, as shown in Table III. We take the Experience Replay Module as the baseline, upon which the following components are considered: CKD applies collaborative distillation loss, PT adds pretext tasks loss, SCL introduces supervised contrastive learning loss, CSS represents the combination of pretext tasks loss and supervised contrastive learning loss.

As shown in Table III, each component contributes positively to the model except for the PT on the MNIST-360 dataset. This is because the samples in the MNIST-360 dataset are rotated at increasing angles, which interferes with the prediction of the pretext tasks. However, its combination with SCL, i.e., CSS, performs better than each of them individually, which proves that the PT and SCL complement each other. Furthermore, when all the components are combined, the best performance is achieved in all settings. This consistent improvement verifies our statement that the joint calibration between CKD and CSS is beneficial for alleviating the deviation, that is, the modules of relation calibration and feature calibration are mutually complementary.

2) The impact of the different numbers of tasks: We further conduct experiments to explore the impact of the different numbers of tasks. We choose sequential CIFAR-100 dataset as an example, which includes 10-split and 20-split settings, that is, dividing the CIFAR-100 dataset into 10 and 20 tasks, respectively. As shown in Table IV, we observe that all competitors except for the upper bound JOINT are sensitive to the number of tasks. As the number of tasks increases from 10 to 20, the performance drops a lot. For example, when buffer sizes are 200, 500 and 5120, the declines are 4.86%, 5.55% and 2.86% in CoCa, respectively. This is due to the increasing number of the tasks leads to the decreasing number of the classes for each task. However, in the case of either a 10-split or 20-split settings, our approach is superior to the other competitors, demonstrating the effectiveness of CoCa framework.

3) The impact of parameters $\omega$ and $\gamma$: Hyper-parameters $\omega$ and $\gamma$ are important in calibrating the relation deviation in Eq. 11. We also select sequential CIFAR-100 dataset as an example, whose results are shown in Fig. 4. As observed
from Fig. 4(a), the different proportions $\omega$ of label propagation have little impact on Relation Calibration Module within the interval of $(0.1, 0.9)$. However, when $\omega$ reaches 1, there is a significant decline. This is because the ensemble output $o^*$ is equal to the reserved output $\hat{o}$, which fails to explore collaborative distillation. Moreover, as shown in Fig. 4(b), $\gamma$ is a sensitive hyper-parameter on balancing the relationship among all classes in collaborative distillation. As we can see, even if $\gamma$ is 0.1, the accuracy improves more than 2% against that of 0. This explains that it is necessary to alleviate the relation deviation in knowledge distillation. However, as $\gamma$ increases, the ensemble output $o^*$ contains less information from the old model, resulting in a dramatic decline in model performance.
E. Visualization Analysis

1) t-SNE Results: To further verify the effectiveness of our CoCa framework on calibrating the feature deviation, we visualize the features for the test set of MNIST-360 dataset, which are shown in Fig. 5. We observe that the t-SNE of all methods are better than that of SGD. However, as evident in Fig. 5(c), classes are not distinguished well and the class boundaries are also not precise and compact through experience replay. As shown in Fig. 5(d) and Fig. 5(e), we can be observed that the features within the class tend to aggregate and the interference of features between different classes are reduced than ER. Figure 5(f) shows the t-SNE corresponding to CoCa, from which we observe that each class is well distinguished and the boundaries of most classes are clear. On the one hand, the complete features are obtained through pretext tasks, leading to the class representations being well spread out. On the other hand, supervised contrastive learning enables the inter-class distance larger and the intra-class distance smaller, which makes the boundaries clearer. Finally, our method takes advantage of the complementary modules that lead to more compact clusters and discriminative class boundaries. It is worth noting that the t-SNE of our method is comparable to that of JOINT, which also proves the effectiveness of our CoCa framework in alleviating the feature deviation.

2) Visualization of confusion matrices: Figure 6 provides the visualization of confusion matrices on the test set of MNIST-360 dataset to give an insight into the effectiveness of our CoCa framework. Among them, diagonal entries represent the accuracy of each class. As shown in Fig. 6(a), SGD is obviously biased towards the last task (8,0). Interestingly, it obtains an easily distinguishable feature for the number 1 (see Fig. 5(a)), but its accuracy is still zero. This proves that the catastrophic forgetting is the result of the feature extractor and classifier. From Fig. 6, we observe that the CoCa has few deviations towards the last task and achieves superior performance among all classes. It indicates that our proposed framework can effectively mitigate the relation deviation.

V. Conclusion

In this paper, we have proposed the CoCa framework to alleviate the relation and feature deviations in GCL by collaborative distillation and self-supervision. Specifically, the collaborative distillation mitigates the relation deviation by exploring ensemble dark knowledge in knowledge distillation to balance the relationship among classes. The collaborative self-supervision is composed of pretext tasks and supervised contrastive learning, which aims at learning complete and discriminative features to alleviate the feature deviation. Extensive experiments have demonstrated that our proposed CoCa framework outperforms the state-of-the-art ones. In future, we consider to leverage online distillation approaches and explore how to select positive samples in contrastive learning.

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Zhong Ji (Senior Member, IEEE) received the Ph.D. degree in signal and information processing from Tianjin University, Tianjin, China, in 2008. He is currently a Professor with the School of Electrical and Information Engineering, Tianjin University. He has authored more than 100 technical articles in refereed journals and conferences. His current research interests include multimedia understanding, zero-shot learning, continual learning, and cross-modal analysis.

Jin Li received the B.S. degree in communication engineering from Hainan University, Haikou, Hainan, China, in 2020. He is currently pursuing the master’s degree with the School of Electrical and Information Engineering, Tianjin University, Tianjin, China. His research interests include computer vision and continual learning.

Qiang Wang received the M.S. degree from the Department of Computer, North China Electric Power University, Baoding, China, in 2019. He is currently pursuing the Ph.D. degree in information and communication engineering with Tianjin University. His current research interests include zero-shot learning and continual learning.

Zhongfei Zhang (Fellow, IEEE) received the B.S. degree (Hons.) in electronics engineering and the M.S. degree in information sciences from Zhejiang University, China, and the Ph.D. degree in computer science from the University of Massachusetts at Amherst, Amherst, MA, USA. He is currently a Professor with the Department of Computer Science, Binghamton University State University of New York, USA. His research interests include machine learning, knowledge discovery, artificial intelligence, computer vision, and pattern recognition.