Contrastive Supervised Distillation for Continual Representation Learning

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Abstract. In this paper, we propose a novel training procedure for the continual representation learning problem in which a neural network model is sequentially learned to alleviate catastrophic forgetting in visual search tasks. Our method, called Contrastive Supervised Distillation (CSD), reduces feature forgetting while learning discriminative features. This is achieved by leveraging labels information in a distillation setting in which the student model is contrastively learned from the teacher model. Extensive experiments show that CSD performs favorably in mitigating catastrophic forgetting by outperforming current state-of-the-art methods. Our results also provide further evidence that feature forgetting evaluated in visual retrieval tasks is not as catastrophic as in classification tasks.

Code at: https://github.com/NiccoBiondi/ContrastiveSupervisedDistillation.

Keywords: Representation Learning · Continual Learning · Image Retrieval · Visual Search · Contrastive Learning · Distillation.

1 Introduction

Deep Convolutional Neural Networks (DCNNs) have significantly advanced the field of visual search or visual retrieval by learning powerful feature representations from data [1,2,3]. Current methods predominantly focus on learning feature representations from static datasets in which all the images are available during training [4,5,6]. This operative condition is restrictive in real-world applications since new data are constantly emerging and repeatedly training DCNN models on both old and new images is time-consuming. Static datasets, typically stored on private servers, are also increasingly problematic because of the societal impact associated with privacy and ethical issues of modern AI systems [7,8].

These problems may be significantly reduced in incremental learning scenarios as the computation is distributed over time and training data are not required to be stored on servers. The challenge of learning feature representation in incremental scenarios has to do with the inherent problem of catastrophic forgetting, namely the loss of previously learned knowledge when new knowledge is assimilated [9,10]. Methods for alleviating catastrophic forgetting has been largely developed in the classification setting, in which

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catastrophic forgetting is typically observed by a clear reduction in classification accuracy \cite{11,12,13,14,15}. The fundamental differences with respect to learning internal feature representation for visual search tasks are: (1) evaluation metrics do not use classification accuracy (2) visual search data have typically a finer granularity with respect to categorical data and (3) no classes are required to be specifically learned. These differences might suggest different origins of the two catastrophic forgetting phenomena. In this regard, some recent works provide some evidence showing the importance of the specific task when evaluating the catastrophic forgetting of the learned representations \cite{16,17,18,19}. In particular, the empirical evidence presented in \cite{16} suggests that feature forgetting is not as catastrophic as classification forgetting. We argue that such evidence is relevant in visual search tasks and that it can be exploited with techniques that learn incrementally without storing past samples in a memory buffer \cite{20}.

According to this, in this paper, we propose a new distillation method for the continual representation learning task, in which the search performance degradation caused by feature forgetting is jointly mitigated while learning discriminative features. This is achieved by aligning current and previous features of the same class, while simultaneously pushing away features of different classes. We follow the basic working principle of contrastive loss \cite{21} used in self-supervised learning, to effectively leverage label information in a distillation-based training procedure in which we replace anchor features with the feature of the teacher model.

Our contributions can be summarized as follows:

1. We address the problem of continual representation learning proposing a novel method that leverages label information in a contrastive distillation learning setup. We call our method Contrastive Supervised Distillation (CSD).
2. Experimental results on different benchmark datasets show that our CSD training procedure achieves state-of-the-art performance.
3. Our results confirm that feature forgetting in visual retrieval using fine-grained datasets is not as catastrophic as in classification.

2 Related Works

Continual Learning (CL). CL has been largely developed in the classification setting, where methods have been broadly categorized based on exemplar \cite{22,23,24,25} and regularization \cite{26,27,20,28}. Only recently, continual learning for feature representation is receiving increasing attention and few works pertinent to the regularization-based category has been proposed \cite{17,18,19}. The work in \cite{17} proposed an unsupervised alignment loss between old and new feature distributions according to the Mean Maximum Discrepancy (MMD) distance \cite{29}. The work \cite{19} uses both the previous model and estimated features to compute a semantic correlation between representations during multiple model updates. The estimated features are used to reproduce the behaviour of older models that are no more available. Finally, \cite{18} addresses the problem of lifelong person re-identification in which the previously acquired knowledge is represented as similarity graphs and it is transferred on the current data through graphs convolutions. While these methods use labels only to learn new tasks, our method leverages labels information to both learn incoming tasks and for distillation.
Reducing feature forgetting with feature distillation is also related to the recent backward compatible representation learning in which newly learned models can be deployed without the need to re-index the existing gallery images [30,31,32]. This may have an impact on privacy as also the gallery images are not required to be stored on servers. Finally, the absence of the cost re-indexing is advantageous in streaming learning scenarios as [33,34].

### 3 Problem Statement

In the continual representation learning problem, a model $M(\cdot; \theta, W)$ is sequentially trained for $T$ tasks on a dataset $D = \{ (x_i, y_i, t_i) | i = 1, 2, \ldots, N \}$, where $x_i$ is an image of a class $y_i \in \{1, 2, \ldots, L\}$, $N$ is the number of images, and $t_i \in \{1, 2, \ldots, T\}$ is the task index associated to each image. In particular, for each task $k$, $M$ is trained on the subset $T_k = D|_{t_i=k} = \{ (x_i, y_i, t_i) | t_i = k \}$ which represents the $k$-th training-set that is composed by $L_k$ classes. Each training-set has different classes and images with respect to the others and only $T_k$ is available to train the model $M$ (memory-free).

At training time of task $k$, in response to a mini-batch $B = \{ (x_i, y_i, t_i) \}_{i=1}^{|B|}$ of $T_k$, the model $M$ extracts the feature vectors and output logits for each image in the batch, i.e., $M(x_i) = C(\phi(x_i))$, where $\phi(\cdot, \theta)$ is the representation model which extracts the feature vector $f_i = \phi(x_i)$ and $C$ is the classifier, which projects the feature vector $f_i$ in an output vector $z_i = C(f_i)$. At the end of the training phase, $M$ is used to index a gallery-set $G = \{ (x_g, y_g) | g = 1, 2, \ldots, N_g \}$ according to the extracted feature vectors $\{ (f_g, y_g) \}_{g=1}^{N_g}$.

At test time, a query-set $Q = \{ x_q | q = 1, 2, \ldots, N_q \}$ is processed by the representation model $\phi(\cdot, \theta)$ in order to obtain the set of feature vectors $\{ f_q \}_{q=1}^{N_q}$. According to cosine distance function $d$, the nearest sample in the gallery-set $G$ is retrieved for each query sample $f_q$, i.e.,

$$f^* = \arg \min_{g=1,2,\ldots,N_q} d(f_g, f_q).$$

### 4 Method

To mitigate the effect of catastrophic forgetting while acquiring novel knowledge from incoming data, we propose a training procedure that follows the teacher-student framework, where the teacher is the model before the update and the student is the model that
is updated. The teacher is leveraged during the training of the student to preserve the old knowledge as old data is not available.

With reference to Fig. 1, at each task $k$, the student is trained on the training-set $\mathcal{T}_k = \{(x_i, y_i, t_i) \mid t_i = k\}$ and the teacher is set as frozen, i.e., not undergoing learning. The loss function that is minimized during the training of the student is the following:

$$\mathcal{L} = \mathcal{L}_{\text{plasticity}} + \mathcal{L}_{\text{stability}}$$

where $\mathcal{L}_{\text{stability}} = 0$ during the training of the model on the first task. In the following, the components of the plasticity and stability loss are analyzed in detail. In particular, we adopt the following notation. Given a mini-batch $\mathcal{B}$ of training data, both the student and the teacher networks produce a set of feature vectors and classifier outputs in response to training images $x_i \in \mathcal{B}$. We refer to as $\{f_i\}, \{z_i\}$ for the feature vectors and classifier outputs of the student, respectively, with $\{f'_i\}, \{z'_i\}$ for the teacher ones, and with $|\mathcal{B}|$ to the number of elements in the mini-batch.

### 4.1 Plasticity Loss

Following [17], during the training of the updated model, the plasticity loss is defined as follows:

$$\mathcal{L}_{\text{plasticity}} = \mathcal{L}_{CE} + \mathcal{L}_{\text{triplet}}$$

with

$$\mathcal{L}_{CE} = \frac{1}{|\mathcal{B}|} \sum_{i=1}^{|\mathcal{B}|} y_i \log \left( \frac{\exp(z_i)}{\sum_{j=1}^{|\mathcal{B}|} \exp(z_j)} \right)$$

$$\mathcal{L}_{\text{triplet}} = \max(||f_i - f_p||_2^2 - ||f_i - f_n||_2^2).$$

$\mathcal{L}_{CE}$ and $\mathcal{L}_{\text{triplet}}$ are the cross-entropy loss and the triplet loss, respectively. The plasticity loss of Eq. 3 is optimized during the training of the model and it is used in order to learn the novel tasks.
4.2 Stability Loss

The stability loss preserves the previously acquired knowledge in order to limit the catastrophic forgetting effect, that is typically performed using the teacher model for distillation. The stability loss we propose is formulated as follows:

\[
\mathcal{L}_{\text{stability}} = \lambda_{\text{KD}} \mathcal{L}_{\text{KD}} + \lambda_{\text{CSD}} \mathcal{L}_{\text{CSD}}
\]

(6)

where \(\lambda_{\text{KD}}\) and \(\lambda_{\text{CSD}}\) are two weights factors that balance the two loss components, namely Knowledge Distillation (KD) and the proposed Contrastive Supervised Distillation (CSD). In our experimental results, we set both \(\lambda_{\text{KD}}\) and \(\lambda_{\text{CSD}}\) to 1. An evaluation of different values is reported in the ablation studies of Sec. 6.

**Knowledge Distillation.** KD [39] minimizes the log-likelihood between the classifier outputs of the student and the soft labels produced by the teacher, instead of the ground-truth labels \(y_i\) used in the standard cross-entropy loss. This encourages the outputs of the updated model to approximate the outputs produced by the previous one. KD is defined as follows:

\[
\mathcal{L}_{\text{KD}} = \frac{1}{|B|} \sum_{i=1}^{|B|} \frac{\exp(z'_i)}{\sum_{j=1}^{|B|} \exp(z'_j)} \log \left( \frac{\exp(z_i)}{\sum_{j=1}^{|B|} \exp(z_j)} \right)
\]

(7)

**Contrastive Supervised Distillation.** We propose a new distillation loss, i.e., the Contrastive Supervised Distillation (CSD) that aligns current and previous feature models of the same classes while simultaneously pushing away features of different classes. This is achieved at training time imposing the following loss penalty:

\[
\mathcal{L}_{\text{CSD}} = -\frac{1}{|B|} \sum_{i=1}^{|B|} \frac{1}{|\mathcal{P}(i)|} \sum_{p \in \mathcal{P}(i)} \log \left( \frac{\exp(f'_i \cdot f_p)}{\sum_{a=1}^{|B|} \exp(f'_a \cdot f_i)} \right)
\]

(8)

where \(\mathcal{P}(i) = \{ (x_p, y_p, t_p) \in B | y_p = y_i \}\) is a set of samples in the batch which belong to the same class of \(x_i\), i.e., the positive samples. Eq. 8 encourage for each class,
the alignment of the student representations to the ones of the same class of the teacher model, which acts as anchors. In Fig. 2, we show the effect of CSD loss on four samples \( \{(x_i, y_i)\}_{i=1}^4 \) with \( y_i \in \{1, 2\} \). Initially (Fig. 2(a)) the feature vectors extracted by the student \( f_i \) (orange samples) are separated from the teacher ones \( f_i' \) (blue samples). CSD clusters together features of the same class moving the student representations, which are trainable, towards the fixed ones of the teacher while pushing apart features belonging to different classes. For the sake of simplicity, this effect is shown just for \( f_1' \) and \( f_3' \). Indeed, \( f_1 \) and \( f_2 \) become closer to \( f_1' \), while \( f_3 \) and \( f_4 \) are spaced apart with respect to \( f_1' \) as they are of class 2. The same effect is visible also for \( f_3' \) which attracts \( f_3 \) and \( f_4 \) and push away \( f_1 \) and \( f_2 \) as shown in Fig. 2(b).

CSD imposes a penalty on feature samples considering not only the overall distribution of features of the teacher model with respect to the student one, but it also clusters together samples of the same class separating from the clusters of the other classes. Our method differs from KD as the loss function is computed directly on the features and not on the classifier outputs resulting in more discriminative representations. CSD also considers all the samples of each class as positive samples that are aligned with the same anchor of the teacher and not pairs (teacher-student) of samples as in [40].

5 Experimental Results

We perform our experimental evaluation on CIFAR-100 [41] and two fine-grained datasets, namely CUB-200 [42] and Stanford Dogs [43]. The CIFAR-100 dataset consists of 60000 32 \times 32 images in 100 classes. The CUB-200 dataset contains 11788 224 \times 224 images of 200 bird species. Stanford Dogs includes over 22000 224 \times 224 annotated images of dogs belonging to 120 species.

The continual representation learning task is evaluated following two strategies. In CIFAR-100, we evenly split the dataset into \( T \) training-set where the model is trained sequentially, using the open-source Avalanche library [44]. The experiments are evaluated with \( T = 2, 5, 10 \). In CUB-200 and Stanford Dogs, following [45][46], we use half of the data to pre-train a model and split the remaining data into \( T \) training-set. CUB-200 is evaluated with \( T = 1, 4, 10 \) while Stanford Dogs with \( T = 1 \).

Implementation Details. We adopt ResNet32 [47] as representation model architecture on CIFAR-100 with 64-dimension feature space. We trained the model for 800 epochs for each task using Adam optimizer with a learning rate of \( 1 \cdot 10^{-3} \) for the initial task and \( 1 \cdot 10^{-5} \) for the others. Random crop and horizontal flip are used as image augmentation. Following [19], we adopt pretrained Google Inception [48] as representation model architecture on CUB-200 and Stanford Dogs with 512-dimension feature space. We trained the model for 2300 epochs for each task using with Adam optimizer with a learning rate of \( 1 \cdot 10^{-5} \) for the convolutional layers and \( 1 \cdot 10^{-6} \) for the classifier. Random crop and horizontal flip are used as image augmentation. We adopt \textsc{Recall@K}[49][45] as performance metric using each image in the test-set as query and the others as gallery.

\footnote{1 https://github.com/arthurdouillard/incremental_learning.pytorch}
Table 1: Evaluation on CIFAR-100 of CSD and compared methods.

| METHOD          | RECALL@1 (1-50) | RECALL@1 (51-100) | Average |
|-----------------|-----------------|-------------------|---------|
| Initial model   | 67.6            | 21.7              | 44.7    |
| Fine-Tuning     | 37.4            | 64.1              | 50.8    |
| LwF [20]        | 64.0            | 59.4              | 61.7    |
| MMD loss [17]   | 61.8            | 60.9              | 61.4    |
| CSD (Ours)      | **65.1**        | **61.6**          | **63.4**|
| Joint Training  | 70.5            | 71.9              | 71.2    |

Fig. 3: Evolution of RECALL@1 on the first task as new tasks are learned on CIFAR-100. Comparison between our method (CSD) and compared methods.

5.1 Evaluation on CIFAR-100

We compare our method on CIFAR-100 dataset with the Fine-Tuning baseline, LwF [20], and [17] denoted as MMD loss. As an upper bound reference, we report the Joint Training performance obtained using all the CIFAR-100 data to train the model.

We report in Tab. 1 the scores obtained with $T = 2$. In the first row, we show the Initial Model results, i.e., the model trained on the first half of data from CIFAR-100. Our approach achieves the highest recall when evaluated on the initial task and the highest recall on the second task between methods trying to preserve old knowledge, being second only to Fine-Tuning that focuses only on learning new data. This results in our method achieving the highest average recall value with an improvement of $\sim 2\%$ RECALL@1 with respect to LwF and MMD loss and $10.4\%$ with respect to the Fine-Tuning baseline. The gap between all the continual representation learning methods and Joint Training is significant ($\sim 8\%$). This underlines the challenges of CIFAR-100 in a continual learning scenario since there is a noticeable difference in the appearance between images of different classes causing a higher feature forgetting.

Fig. 3(a) and Fig. 3(b) report the evolution of RECALL@1 on the initial task as new tasks are learned with $T = 5$ and $T = 10$, respectively. In both experiments, our approach does not always report the highest scores, but it achieves the most stable trend.
obtaining the best result as the training end. This confirms that our approach is effective also when the model is updated multiple times.

### 5.2 Evaluation on Fine-grained Datasets

We compare our method on CUB-200 and Stanford Dogs datasets with the Fine-Tuning baseline, MMD loss [17], and [19] denoted as Feature Estimation. As an upper bound reference, we report the Joint Training performance obtained using all the data to train the model.

We report in Tab. 2 the scores obtained with $T = 1$ on the fine-grained datasets. On Stanford Dogs, our approach achieves the highest recall when evaluated on the initial task and comparable result with other methods on the final task with a gap of only 0.2% with respect to Fine-Tuning that focus only on learning new data. This results in our method achieving the highest average recall value with an improvement of 0.5% \textsc{Recall@1} concerning Feature Estimation, 0.8% for MMD loss, and 3.4% for Fine-Tuning. On the more challenging CUB-200 dataset, we obtain the best \textsc{Recall@1} on both the initial and the final task outperforming the compared methods. Our method achieves the highest average recall value with an improvement of 2.1% \textsc{Recall@1} with respect to Feature Estimation, 2.9% for MMD loss, and 5.8% for Fine-Tuning.

#### Table 2: Evaluation on Stanford Dogs and CUB-200 of CSD and compared methods.

| Method          | STANFORD DOGS | CUB-200 |
|-----------------|---------------|---------|
|                 | Recall@1 (1-60) | Recall@1 (61-120) | Recall@1 Average | Recall@1 (1-100) | Recall@1 (101-200) | Recall@1 Average |
| Initial model   | 81.3          | 69.3    | 75.3 | 79.2 | 46.9 | 63.1 |
| Fine-Tuning     | 74.0          | 83.7    | 78.8 | 70.2 | 75.1 | 72.7 |
| MMD loss [17]   | 79.5          | 83.4    | 81.4 | 77.0 | 74.1 | 75.6 |
| Feat. Est. [19] | 79.9          | 83.5    | 81.7 | 77.7 | 75.0 | 76.4 |
| CSD (Ours)      | **80.9**      | **83.5** | **82.2** | **78.6** | **78.3** | **78.5** |
| Joint Training  | 80.4          | 83.1    | 81.7 | 78.2 | 79.2 | 78.7 |

Fig. 4: Evolution of \textsc{Recall@1} on the first task as new tasks are learned on CUB-200. Comparison between our method (CSD) and compared methods.
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Differently from CIFAR-100, on fine-grained datasets, there is a lower dataset shift between different tasks leading to a higher performance closer to the Joint Training upper bound due to lower feature forgetting.

We report in Fig. 4(a) and Fig. 4(b) the challenging cases of CUB-200 with \( T = 4 \) and \( T = 10 \), respectively. These experiments show, consistently with Tab. 2, how our approach outperforms state-of-the-art methods. In particular, with \( T = 10 \) (Fig. 4(b)), our method preserves the performance obtained on the initial task during every update. CSD largely improves over the state-of-the-art methods by almost 20% - 25% with respect to [19] and [17] achieving similar performance to the Joint Training upper bound. By leveraging labels information for distillation during model updates, CSD provides better performance and favorably mitigates the catastrophic forgetting of the representation compared to other methods that do not make use of this information.

6 Ablation Study

**Loss Components.** In Fig. 5, we explore the benefits given by the components of the loss in Eq. 2 (i.e., CE, triplet, KD, and CSD) and their combinations in terms of RECALL@1 on CUB-200 with \( T = 10 \). To observe single component performance, we analyze the trend of RECALL@1 on both the current task and previous ones evaluated jointly. When CSD is used, (i.e., CE+CSD, CE+KD+CSD, CE+triplet+CSD, CE+triplet+KD+CSD), we achieve higher RECALL@1 and maintain a more stable trend with respect to others. This underlines how CSD is effective and central to preserve knowledge and limit feature forgetting across model updates.

**Loss Components Weights.** Finally, in Tab. 3, we analyze the influence of the stability loss components varying the parameters \( \lambda_{ KD } \) and \( \lambda_{ CSD } \) of Eq. 6 on CUB-200 with \( T = 1 \). The table shows the RECALL@1 obtained on the first task, on the final task, and the average between them after training the model. CSD best performs when \( \lambda_{ KD } = \lambda_{ CSD } = 1 \), obtaining the highest average RECALL@1.
7 Conclusions

In this paper, we propose Contrastive Supervised Distillation (CSD) to reduce feature forgetting in continual representation learning. Our approach tackles the problem without storing data of previously learned tasks while learning a new incoming task. CSD allows to minimize the discrepancy of new and old features belonging to the same class, while simultaneously pushing apart features from different classes of both current and old data in a contrastive manner. We evaluate our approach and compare it to state-of-the-art works performing empirical experiments on three benchmark datasets, namely CIFAR-100, CUB-200, and Stanford Dogs. Results show the advantages provided by our method in particular on fine-grained datasets where CSD outperforms current state-of-the-art methods. Experiments also provide further evidence that feature forgetting evaluated in visual retrieval tasks is not as catastrophic as in classification tasks.

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