A Simple Baseline that Questions the Use of Pretrained-Models in Continual Learning

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Abstract

With the success of pretraining techniques in representation learning, a number of continual learning methods based on pretrained models have been proposed. Some of these methods design continual learning mechanisms on the pre-trained representations and only allow minimum updates or even no updates of the backbone models during the training of continual learning. In this paper, we question whether the complexity of these models is needed to achieve good performance by comparing them to a simple baseline that we designed. We argue that the pretrained feature extractor itself can be strong enough to achieve a competitive or even better continual learning performance on Split-CIFAR100 and CoRe 50 benchmarks. To validate this, we conduct a very simple baseline that 1) use the frozen pretrained model to extract image features for every class encountered during the continual learning stage and compute their corresponding mean features on training data, and 2) predict the class of the input based on the nearest neighbor distance between test samples and mean features of the classes; i.e., Nearest Mean Classifier (NMC). This baseline is single-headed, exemplar-free, and can be task-free (by updating the means continually). This baseline achieved 88.53% on 10-Split-CIFAR-100, surpassing most state-of-the-art continual learning methods that are all initialized using the same pretrained transformer model. We hope our baseline may encourage future progress in designing learning systems that can continually add quality to the learning representations even if they started from some pretrained weights.

1 Introduction

Conventional machine learning models struggle to perform well when the i.i.d. assumption is violated in the real world, where data arrives sequentially from shifting distributions/tasks over time. These models suffer from catastrophic forgetting of earlier tasks[15, 10]. Continual learning, in which the agent is expected to learn new tasks without forgetting the old ones, has been studied extensively as a potential solution to this issue. Early approaches start training with a model without prior knowledge, continually adapt the model for future tasks, and prevent forgetting by replaying the data, designing the penalization of the model parameter updates, and/or, dynamically increasing model parameters to incorporate new knowledge.

The use of large-scale datasets, such as ImageNet-1k[23] and ImageNet-21k [22] and pretraining [24] has led to significant advances. With sufficient and diverse data, the output features of a pretrained model generalize well to a vast array of tasks, greatly boosting the performance of challenging learning regimes such as continual learning. As a result, pretrained models have been deployed as feature extractors, and continual learning techniques are applied directly on the feature level. These methods imply that pretrained models provide general and coarse features that need to be task-specifically fine-tuned, where forgetting occurs. However, [20] stated large-scale pretrained models

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have excellent classification performance to data outside of the pretrained distribution even without training. We are questioning whether these pretrained features can be competitive for downstream tasks and whether sophisticated continual learning techniques are indeed needed to achieve a good performance on the studied continual learning benchmarks.

To answer these questions, we implement a simple baseline in continual learning. We use a frozen pretrained model to extract features for the training set and compute mean features to represent each class. During the testing time, we make predictions based on the distance between the test samples and class mean features. Our results are surprisingly outperforming SOTA methods using the same pretrained backbone network. We achieve 88.53% Average Accuracy at the end of the learning sequence of Split CIFAR100 compared to 83.83% of L2P[27], and 83.23% on the evaluation task of CoRe50 compared to 78.33% of L2P. This implies that the pretrained models provided quality learning representations that are robust under distribution shifts. We also present the experimental results on two more diverse benchmarks, 5-dataset and Split-ImageNet-R, to emphasize the importance of the benchmark to evaluate continual learning methods with pretrained model. The results also show competitive performance outperforming most methods.

Our proposed baseline is single-headed, task-free, and exemplar-free as an additional bonus. We argue that this is a simple yet powerful baseline that every continual learning method should compare against. The intentions of these properties are to make less use of task labels (which are unrealistic in practice) and replay data (which raises privacy concerns) in the techniques. We observe that some prior works sometimes outperform this baseline, but at the sacrifice of one or more of these characteristics. There are few comparable approaches with ours when all the conditions align. We hope that this work sheds some light on examining the practicality of pertraining in continual learning and whether we are on improving the learning representation quality continually.

2 Related Work

Continual learning with pre-trained models Continual learning methods generally trained feature extractors from scratch and constrained the drift in feature representation [10, 16]. Recently, the usage of pre-trained models has attracted more attention in continual learning. [2] viewed the first task as a pre-training stage and froze the feature representation after the first task. [7] found that a larger size of data in the first task and self-supervised pre-training helped to decrease catastrophic forgetting. [12] empirically analyzed the effect of training the last layer with a fixed feature extractor. [18] studied foundation models and replay of frozen latent features to overcome catastrophic forgetting. Recently [27] proposed to use prompt based fine-tuning with a pre-trained transformer [5, 25] and compared it with other methods in the same initialization. We adopt this strategy and point out that classifier learning actually reduced the power of representations learned by the pre-trained model.

Task-aware/free continual learning Task incremental method requires the task identifiers of the samples during the inference, which reduces the practical application of these methods, whereas class-incremental methods do not require those. However, task-aware/free methods suffer from class recency bias. To overcome such recency bias, BiC[29] proposed to add a final layer that reduces the final bias. LUCIR [9] proposed to use a balanced fine-tuning to train the classifier after freezing feature representation. Our method also focuses on this problem and uses the simple nearest mean classifier on top of pre-trained transformer.

Exemplar-free continual learning Earlier methods were proposed to store raw data, learned features, or generated features from previous tasks. Since the replay mechanism such as ER [4] is orthogonal to architecture-based and regularization-based methods, they are widely adopted in other methods to improve performance. Recently there has been an increased interest in exemplar-free continual learning to account for privacy concerns in storing raw samples and storage concerns. iCaRL [21] introduced the method of using exemplars for continual learning and selected exemplars close to the class means. Our baseline follows a similar strategy but only stores the class-mean in feature space which save the storage by reducing the number of latent variables to keep per class.

3 Methodology

Problem Setup We adopt the standard continual learning scenario where a model learns from a non-i.i.d. data stream, represented as $\mathcal{D}_1, ..., \mathcal{D}_T$, where $\mathcal{D}_t = \{(x_i^t, y_i^t)\}_{i=1}^{N_t}$ is the task-specific subset, $x_i^t \in \mathbb{R}^{w \times h \times c}$ is an image input and $y_i^t \in \mathbb{Z}$ is its corresponding label. The goal of continual

learning is to learn a function f_θ which maps the input x to the label y from an arbitrary task seen so far. We focus on two scenarios. In the class-incremental setting, each subset $\mathcal{D}_t$ contains a disjoint class label set. In the domain-incremental setting, the subsets share the class labels, but the domain of the input distributions varies over time.

Nearest Mean Classifier (NMC) We decouple the goal of continual learning f_θ into two steps. The first step is to learn the representation h_ψ and the next is to learn the classifier g_ϕ. We directly adopt a pre-trained vision transformer model as our feature representation without training. For the classifier, inspired by [21, 17] we use the nearest mean classification strategy. During the training stage of task t, we calculate the mean features of a class in $\mathcal{D}_t$

$$\mu_k = \frac{1}{|C_k|} \sum_{x \in C_k} h(x) \ , \tag{1}$$

where C_k denotes the set of training samples belonging to class k. Only class mean features are saved in the memory and will be used during evaluation. At the test time of task t, a test sample's feature is extracted by the pretrained model, and the predicted class label is taken as the class whose mean features is the closest (over all the seen classes so far) to the feature of a test sample.

$$\hat{y} = \underset{k}{\text{argmin}} ||h(x) - \mu_k|| \tag{2}$$

4 Experiments

We follow the experimental setup used in [27] to evaluate our method for a fair comparison. We test our method in class incremental learning, where new sets of classes are introduced to the model, and domain incremental learning, where classes remain the same and the domain changes; see Sec 3.

Datasets We evaluate our baseline on four common continual learning benchmarks, Split- CIFAR100 [11] , 5-datasets [6] and Split-ImageNet-R [8] in the class incremental learning setting. As proposed by [27] and [26]. Split-CIFAR-100 contains 10 tasks with 10 classes for each task. The 5-dataset benchmark concatenates 5 datasets, MNIST, SVHN, notMNIST , FashionMNIST and CIFAR10, with each dataset forming one task. Split ImageNet-R is a newly proposed dataset for continual learning by [26]. It consists of 200 classes which are randomly divided into 10 tasks. It contains the same object types however presented in different styles such as cartoon , graffiti and origami. These variations make the continual learning more challenging. For the domain incremental learning setting, we use CoRe50 proposed by [14]. It contains 50 objects collected in 11 distinct domains(tasks). 8 domains were faced and learned incrementally while the test is performed on the remaining three domains. Since a single test task is used, we do not report forgetting and joint training results in that scenario.

Evaluated Methods. For our approach (`Ours`), we employ the widely used ViT-B/16[5] model pre-trained on ImageNet-21k [24] provided by `timm` library [28]. We mainly compare our baseline with the recent L2P [27] which adopts the pretrained model as ours and learns a prompt pool with a prompt selection mechanism to modify the pretrained representations. We also consider popular continual learning methods including regularization-based methods (LwF[13] , EWC [10]) and rehearsal-based methods (ER[4], GDumb[19], BiC [29], DER++ [1] and Co^{2}L [3]). We present joint training results where the training data is, i.i.d. distributed among the whole benchmark with no task split. FT-frozen adds a fully-connected layer on top of the frozen feature extractor as the classification, and FT allows end-to-end training on the feature extractor. Note that this is different from our baseline, as we use NMC classifier and build it incrementally.

Results Table 1, 4, and 2 report the performance of continual learning in incremental setting in Average Accuracy at the end of the learning sequence of Split-CIFAR100, Split-ImageNet-R, and the 5-dataset respectively. Table 4 shows the results of the continual learning in domain incremental setting on CoRe50[14]. The results are grouped based on the use of replay sample. Our simple baseline achieves the best performance on Split CIFAR-100 and CoRe50 while being the second best on Split-ImageNet-R and 5-dataset benchmarks. Our results on Split-CIFAR-100 are even better than methods that use replay samples. Concretely, our baseline achieves 88.53% with a 0 buffer size, which is more than 4.7% and 2.22% better than the runner-up and significantly more complicated L2P with no exemplars and L2P with 50 exemplars/class buffer, respectively. This suggests that pre-trained transformer offers a strong representation that achieves competitive performance. We think that the main reason for a possible inferior performance could be the ineffective design of the continual learning mechanisms compared to the robust features provided by the pretrained model. Such a

Table 1: Continual learning performance expressed in Average Accuracy and Forgetting at the end of the learning sequence of CIFAR-100[11]. All methods are initialized with pretrained weights for a fair comparison. Our baseline outperforms all the methods in this benchmark.

Method	Buffer size	Average Acc	Forgetting
FT - frozen	0	17.72	59.09
FT	0	33.61	86.87
EWC[10]	0	47.01	33.27
LwF [13]	0	60.69	27.77
L2P [27]	0	83.83	7.63
Ours	0	**88.53**	-
ER [4]	50/class	82.53	16.46
GDumb [19]	50/class	81.67	-
BiC [29]	50/class	81.42	17.31
DER++ [1]	50/class	83.94	14.55
Co2L [3]	50/class	82.49	17.48
L2P [27]	50/class	86.31	5.83
Joint	-	90.85	-

Table 2: Continual learning performance expressed in Average Accuracy and Forgetting at the end of the learning sequence of the 5-dataset benchmark [6]. All methods are initialized with pretrained weights of transformer for a fair comparison. Our baseline performs competitively with the exemplar-free methods in this benchmark

Method	Buffer size	Average Acc	Forgetting
FT - frozen	0	39.49	42.62
FT	0	20.12	94.63
EWC[10]	0	50.93	34.94
LwF [13]	0	47.91	38.01
L2P [27]	0	**81.14**	4.64
Ours	0	79.84	-
ER [4]	50/class	84.26	12.85
GDumb [19]	50/class	70.76	-
BiC [29]	50/class	85.53	10.27
DER++ [1]	50/class	84.88	10.46
Co2L [3]	50/class	86.05	12.28
L2P[27]	50/class	**88.95**	4.92
Joint		93.93	

Table 3: Continual learning performance in Average Accuracy at the evaluation task of CoRe50 [14]. All methods are initialized with pretrained weight for fair comparison

Method	Buffer size	Test Acc
EWC[10]	0	74.82
LwF[13]	0	75.45
L2P[27]	0	78.33
Ours	0	**83.23**
ER[4]	50/class	80.1
GDumb[19]	50/class	74.92
BiC[29]	50/class	79.28
DER++[1]	50/class	79.7
Co2L[3]	50/class	79.75
L2P[27]	50/class	81.07

Table 4: Continual learning performance in Average Accuracy and Forgetting at the end of the learning sequence of the Split-ImageNet-R[8] benchmark. All methods are initialized with pretrained weights for fair comparison.

Method	Buffer size	Average Acc.	Forgetting
FT - frozen	0	39.49	42.62
FT	0	28.87	63.80
EWC [10]	0	35.00	56.16
LwF [13]	0	38.54	52.37
L2P [27]	0	61.57	9.73
Ours	0	**65.99**	-
ER [4]	5000	65.18	23.31
GDumb [19]	5000	65.90	-
BiC [29]	5000	64.63	22.25
DER++ [1]	5000	**66.73**	20.67
Co2L [3]	5000	65.90	23.36
Joint	-	79.13	-

model is pretrained on a large and diverse dataset, which may have already captured most of the distribution properties in the evaluation benchmarks. Then a desired continual learning mechanism needs to further encourage the model to produce the task-invariant features specific to the deployed benchmark. Our nearest neighbor baseline is also competent among exemplar-free methods on Split-ImageNet-R and 5-datasets benchmarks, which is more diverse than CIFAR-100 and CoRe50. However, methods with higher buffer sizes and finely designed continual learning mechanisms do improve the representations extracted from pretrained models.

5 Conclusion

In this work, we explore the representational capacity of large-scale pre-trained models in continual learning settings. We provide simple nearest neighbor baseline experiments on four benchmarks, showing competitive performance to more sophisticated state-of-the-art continual learning methods which also leverage the same pretrained models. We agree that using pretrained weights can be a reasonable practice even in continual learning. However, to show real progress in continual learning systems, we need to focus more on building methods that can continually add quality to the learning representations. A desired continual learning algorithm shall go significantly beyond the knowledge embedded in the pretrained model. Another important aspect is the considered benchmarks for evaluating continual learning methods. Such benchmarks need to be sufficiently challenging and different from the data distributions employed for pretrained models.

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