Generative Feature Replay with Orthogonal Weight Modification for Continual Learning

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Abstract

The ability of intelligent agents to learn and remember multiple tasks sequentially is crucial to achieving artificial general intelligence. Many continual learning (CL) methods have been proposed to overcome catastrophic forgetting. Catastrophic forgetting notoriously impedes the sequential learning of neural networks as the data of previous tasks are unavailable. In this paper we focus on class incremental learning, a challenging CL scenario, in which classes of each task are disjoint and task identity is unknown during test. For this scenario, generative replay is an effective strategy which generates and replays pseudo data for previous tasks to alleviate catastrophic forgetting. However, it is not trivial to learn a generative model continually for relatively complex data. Based on recently proposed orthogonal weight modification (OWM) algorithm which can keep previously learned input-output mappings invariant approximately when learning new tasks, we propose to directly generate and replay feature. Empirical results on image and text datasets show our method can improve OWM consistently by a significant margin while conventional generative replay always results in a negative effect. Our method also beats a state-of-the-art generative replay method and is competitive with a strong baseline based on real data storage.

1 Introduction

Deep learning has achieved remarkable levels of performance for AI, exceeding the abilities of human experts on several particular tasks. However, neural networks (NN) are prone to suffer from catastrophic forgetting [McCloskey and Cohen, 1989; French, 1999] when learning multiple tasks in a sequential manner. This phenomenon results from the interference between the knowledge of previous tasks and current task because the data of previous tasks are unavailable and leads to significant degradation of previous tasks’ performance. In contrast, humans excel at learning new skills and accumulating knowledge continually throughout their lifespan. Continual learning (CL) [Parisi et al., 2019] aims to bridge this gap and has become an important challenge of AI research. It allows intelligent agents to reuse and transfer old knowledge meanwhile meets the real-world situation where training data are hardly available simultaneously.

According to whether task identity is provided and whether it must be inferred during test, there are mainly three continual learning scenarios [van de Ven and Tolias, 2018; Hsu et al., 2018] i.e. task incremental learning, domain incremental learning and class incremental learning. Class incremental learning (CIL) is the most challenging scenario in which the classes of each task are disjoint and the model is trained to distinguish classes of all tasks with a shared output layer a.k.a. “single-head”. In this paper we focus on CIL.

CIL corresponds to the problem of learning new classes of objects incrementally which is widespread in real-world applications. As the data of old classes are unavailable and the class distribution is changing continually, the shared output layer can exacerbate the forgetting of previous tasks. Some CL methods [Kirkpatrick et al., 2017; Li and Hoiem, 2018] performing well in the other two scenarios almost totally get failed in CIL [van de Ven and Tolias, 2018; Hsu et al., 2018]. A naive approach to alleviate this problem is to store a subset of real data of previous tasks and replay them to classifier when learning new tasks [Rebuffi et al., 2017; Nguyen et al., 2018]. However it violates the main protocol in CL that only data of current task are available. Data privacy concerns also question the practical value of real data replay methods. In this paper, we aim to design CIL method without any real data storage.

Inspired by complementary learning systems (CLS) theory [O’Reilly and Norman, 2002] about biological mechanisms, generative replay [Shin et al., 2017] approach has made some progress in CIL. Instead of storing the real data, a generative model, such as generative adversarial networks (GANs) [Goodfellow et al., 2014b] or variational autoencoder (VAE) [Kingma and Welling, 2014] is trained to learn the data distribution of previous tasks. During training, both the real data of the current task and the synthesized data sampled from the generator are fed into classifier. As the synthesized data represent the distribution of old classes approximately, classifier can retain the knowledge of previous tasks. While learning the new knowledge, the generator are trained...
in the same manner to prevent catastrophic forgetting. Despite generative replay works well on simple datasets such as MNIST, it is far from solving CIL completely. As pointed out in [Lesort et al., 2019], training a generative model in the CL scenario is not as easy as training a generative model in a joint training manner. For example, generative replay totally fails when being applied on CIFAR10, a real-world image dataset [Lesort et al., 2019]. Hu et al. [2019] also find it is impractical to replay text data with a generative model.

Recently, orthogonal weight modification (OWM) [Zeng et al., 2019] algorithm has been proposed which is applicable in the above three CL scenarios and can be considered as the state-of-the-art method for CIL. The main idea behind OWM algorithm is that to protect previously learned knowledge, we modify the neural network’s weights only in the direction orthogonal to the subspace spanned by all previous inputs fed into the network. In this way, during training new inputs, the network can keep the learned input-output mappings invariable. Zeng et al. [2019] provide an online approximate iterative method to update the direction orthogonal to the input space so that OWM is compatible with mini-batch optimization. As OWM algorithm only introduces an extra modification operation on gradient of weights during training thus no task information is required during test, it can be used in CIL.

In this paper, on the basis of OWM algorithm, we propose to generate and replay feature instead of raw data to improve the performance of class incremental learning. Specifically, we utilize OWM algorithm on classifier meanwhile we train a generative model to learn the distribution of the feature of penultimate layer. When training the subsequent tasks, generated pseudo features are paired with the new features in the same layer and fed into the last fully connected (FC) layer. Due to the effect of OWM, the features in each layer are stable which makes the feature replay feasible potentially.

Our motivation is three-fold: Firstly, although OWM can keep the ability of distinguishing the classes within one task, data from classes that belong to different tasks are never fed into classifier simultaneously. Therefore classifier is prone to confuse about task identity when classifying over all classes. Replaying data of previous tasks can alleviate this problem. Secondly, as raw data contain many details not related to class information, learning to continually generate real-world data is hard. However, the distribution of high-level features are relatively simple, which lessens the difficulty of training the generator. Thirdly, almost all NN-based classifiers’ output layers are full-connected so that generating the feature of penultimate layer is a universal strategy. Experimental results on several real-world image and text datasets show the superiority of proposed method to state-of-the-art CIL methods, including OWM.

2 Related Work

The study of catastrophic forgetting in neural networks originated in the 1980s [McCloskey and Cohen, 1989; Robins, 1993]. Under the revival of neural networks, overcoming catastrophic forgetting in continual learning setting has drawn much attention again [Goodfellow et al., 2014a; Rusu et al., 2016; Kirkpatrick et al., 2017]. In this section, we mainly review recent continual learning literature which is closely related to our work. Contemporary continual learning strategies can be divided roughly into four categories which are regularization, task-specific, replay and subspace respectively. It should be noted that some existing CL works propose hybrid approaches incorporating more than one strategy.

The most famous regularization method is elastic weight consolidation (EWC) [Kirkpatrick et al., 2017] which adds a weighted L2 penalty term on NN’s parameters. The weight of L2 term is defined as Fisher’s information which can measure the importance of each parameter to previously learned knowledge. Li and Hoiem [2018] propose another type of regularization method which encourages the current classifier’s output probabilities on old classes to approximate the outputs of the old classifier. Such regularization methods are effective on task/domain incremental learning scenarios, however when being applied to CIL scenario [van de Ven and Tolias, 2018; Hsu et al., 2018], they almost totally fail.

Task-specific methods aim at prevent knowledge interference by establishing task-specific modules for different tasks. The task-specific modules can be hidden units [Masse et al., 2018], network parameters [Mallya and Lazebnik, 2018] and dynamically growing sub-networks [Rusu et al., 2016]. This type of strategy is designed for task incremental learning. During test these methods need task identity to choose corresponding task-specific modules therefore they are not applicable for class incremental learning.

Replay (also called rehearsal) strategy is initially proposed to relearn a subset of previously learned data when learning the current task [Robins, 1993]. Some recent works [Rebuffi et al., 2017; Wu et al., 2019] storing a subset of old data fall into this category which we call real data replay. Real data replay not only violates the continual learning requirement that old data are unavailable, but also is against the notion of bio-inspired design. According to CLS theory [O’Reilly and Norman, 2002] the hippocampus encodes and replays recent experiences to help the memory in the neocortex consolidate. Some evidence illustrates hippocampus works like a generative model than a replay buffer, which has inspired the proposal of deep generative replay (DGR) [Shin et al., 2017]. Generative replay utilizes GAN framework to train a generator to learn the distribution of old data. When learning new tasks the pseudo data generated by the generator are replayed to classifier. Due to the power of approximating distribution of GAN, replayed data reduce the shift of data distribution, especially in CIL scenario, thus can alleviate catastrophic forgetting. As the generator is also trained continually with replayed data, DGR may break down when it encounters complex real-world data [Hu et al., 2019; Lesort et al., 2019]. A remedy is to encode the raw data into features with a feature extractor pre-trained on large-scale datasets and replay features [Hu et al., 2019; Xiang et al., 2019]. However, such a pre-trained model is not often easily obtained. In addition, learning from scratch for moderately large data can more accurately reflect the CL method’s performance. In contrast, we firstly propose a successful method to replay features without pre-training.

The last strategy we call subspace methods [He and Jaeger, 2018; Zeng et al., 2019] retains previously learned knowl-
by back propagation (BP) during training $T_n$. When testing on the previous tasks $T_{<n}$, the FC layer’s output $x_{out}^{<n,n}$ is deviated from the optimum value $x_{out}^{<n,n-1}$ after learning $T_{n-1}$, i.e., $x_{out}^{<n,n} = W^{n-1}x_{out}^{<n,n-1} = W^{n-1} - \lambda Dw_{BP}^{n-1} x_{in}^{<n,n-1} = x_{out}^{<n,n-1}$. The deviation accumulates across layers and causes catastrophic forgetting on previous tasks.

To overcome this, Zeng et al. [2019] have developed OWM algorithm to project $\Delta W_{BP}^{n-1}$ to the subspace orthogonal to the input of all previous tasks: $P_{s} = I - A_{n}(A_{n}^{T}A_{n} + \alpha I)^{-1}A_{n}^{T}$, where matrix $A_{n} = [x_{1}, \ldots, x_{n-1}]$ consists of input vectors which has been trained before as its columns$^1$ and $\alpha$ is a small constant to resist in noise. The gradient is modified with the projector $P_{s}$: $\Delta W_{n-1}^{BP} = \Delta W_{n-1}^{BP} P_{s}$. Because for any input $x_{in}^{<n,n}$ in the input space $A_{n}$ we have $A_{n}(A_{n}^{T}A_{n} + \alpha I)^{-1}A_{n}^{T}x_{in}^{<n,n} \approx x_{in}^{<n,n}$ OWM can keep the output invariant approximately after gradient descent update:

$$x_{out}^{<n,n} = W^{n}x_{in}^{<n,n} = W^{n-1}x_{out}^{<n,n-1} - \lambda Dw_{OWM}^{n-1}x_{in}^{<n,n} = x_{out}^{<n,n-1} - \lambda Dw_{BP}^{n-1}P_{s}x_{in}^{<n,n} = x_{out}^{<n,n-1} - \lambda Dw_{BP}^{n-1}(I - A_{n}(A_{n}^{T}A_{n} + \alpha I)^{-1}A_{n}^{T})x_{in}^{<n,n} \approx x_{out}^{<n,n-1}$$

Such a property makes the network capable of maintaining previously learned input-output mappings meanwhile the new tasks can be learned. The extra operation is computing projector $P$ and projected gradient $\Delta W_{OWM}$ before running gradient descent. We can calculate $P$ in an efficient online manner as described in [Zeng et al., 2019]:

$$P^{k} = P^{k-1} - (\alpha + \bar{x}_{k}^{T}P^{k-1}\bar{x}_{k})^{-1}P^{k-1}\bar{x}_{k}\bar{x}_{k}^{T}$$

where $k$ indexes the mini-batch and $\bar{x}_{k}$ is the mean of the $k$-th mini-batch’s inputs. Although we use FC layer to explain here, OWM algorithm can be applied to other NNs such as convolution neural networks (CNN). See the original paper [Zeng et al., 2019] for more details about OWM.

### 3.2 Generative Feature Replay

Although OWM is state-of-the-art method in CIL scenarios, projected gradients can mainly protect the knowledge of distinguishing the classes in the same task. The classifier potentially has confusion about the task identity during test as the data from different tasks are never trained together, which is the major difficulty in CIL.

To alleviate this problem, we propose Generative Feature Replay (GFR), which replay the penultimate layer feature $h$ instead of the raw data to improve OWM. We use an Auxiliary Conditional GAN (AC-GAN) [Odena et al., 2017] model as generator, which allows conditional generation with labels and has been proven to work better than vanilla GAN for continual learning [Wu et al., 2018]. We call the existing generative replay as Generative Input Replay (GIR).

In our framework, the whole model is comprised of a classifier $C(\theta^{C})$, a generator $G(\theta^{G})$ and a discriminator $D(\theta^{D})$.

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$^1$Without loss of generality, here we treat $x_{i}$ as a vector for brevity, which means each task has only one input data.
The discriminator gives two outputs: $D_{cls}$ means the probability that the input is real, like vanilla GANs and $D_{dis}$ predicts the input’s class. The generator takes a noise $z$ and a class label $c$ as inputs. We further divide $C(\theta^C_n)$ into two parts: the last FC layer $F(\theta^F_n)$ and feature extractor $E(\theta^E_n)$. As $C$ is trained with OWM, given the inputs of previous tasks, each layer’s outputs, including $h$ remain stable when learning new tasks continually. Thus we can employ the AC-GAN to generate $h$ for replay, which can reduce the difficulty of training the generator compare with GIR.

We implement AC-GAN with WGAN-GP technique [Gulrajani et al., 2017] for more stable training. The loss functions which $G(\theta^G_n)$ and $D(\theta^D_n)$ are trained to minimize when training the $n$-th task are as follows:

$$L(\theta^G_n) = -L_{GAN}(\theta^G_n) + L_{CLS}(\theta^G_n)$$

$$L(\theta^D_n) = L_{GAN}(\theta^D_n) + L_{CLS}(\theta^D_n) + \lambda_{GP}L_{GP}$$

The $L_{GAN}$ is from $D_{dis}$ to discriminate real and fake features:

$$L_{GAN} = -\mathbb{E}_{(x,y)\sim X_n}[D_{dis}(E(x; \theta^E_n); \theta^D_n)] - \mathbb{E}_{z\sim p_z, c\sim p_{c1:n-1}}[D_{dis}(G(z, c; \theta^G_{n-1}); \theta^D_n)] + \mathbb{E}_{z\sim p_z, c\sim p_{c_n}}[D_{dis}(G(z, c; \theta^G_{n-1}); \theta^D_n)]$$

where $X_n$ is the real data distribution of $n$-th task. $p_z$ is the noise distribution. $p_{c1:n-1}$ and $p_{c_n}$ represent label distribution for the first $n - 1$ tasks and the $n$-th task respectively. The first term refers to real features of data in $X_n$ while the third term corresponds to fake features generated by the current generator $G(\theta^G_n)$. To allow $G(\theta^G_n)$ to be able to generate features of previous tasks, the fake features generated by the old generator $G(\theta^G_{n-1})$ are also considered as real features which corresponds to the second term. Similarly, the $L_{CLS}$ also has three parts:

$$L_{CLS} = \mathbb{E}_{(x,y)\sim X_n}[L_{CE}(D_{cls}(E(x; \theta^E_n); \theta^D_n), y)] + \mathbb{E}_{z\sim p_z, c\sim p_{c1:n-1}}[L_{CE}(D_{cls}(G(z, c; \theta^G_{n-1}); \theta^D_n), c)] + \mathbb{E}_{z\sim p_z, c\sim p_{c_n}}[L_{CE}(D_{cls}(G(z, c; \theta^G_{n-1}); \theta^D_n), c)]$$

where $L_{CE}$ means the cross-entropy loss. Here discriminator and generator are both trained to minimize the classification loss for all real and fake features. $L_{GP}$ is gradient penalty term in WGAN-GP [Gulrajani et al., 2017] and we set $\lambda_{GP} = 10$ in all experiments. It should be noted that when training $(\theta^G_n, \theta^D_n), \theta^C_n = (\theta^E_n, \theta^F_n)$ and $\theta^G_{n-1}$ are fixed.

Generator $G(\theta^G_n)$ is used to generate replayed features of the first $n$ tasks $\tilde{h}_n = G(z, c; \theta^G_n)$ when training classifier in $T_{n+1}$. The loss function of classifier is as follows:

$$L(\theta^E_{n+1}, \theta^F_{n+1}) = \mathbb{E}_{(x,y)\sim X_{n+1}}[L_{CE}(C(x; \theta^E_{n+1}, \theta^F_{n+1}), y)] + \mathbb{E}_{z\sim p_z, c\sim p_{c1:n}}[L_{CE}(F(\tilde{h}_n; \theta^E_n), F(h_n; \theta^F_n))]$$

where the two terms correspond to the loss of true data and replayed features $\tilde{h}_n$ respectively. In the second term, we use the probabilities predicted by the old classifier $F(\theta^F_n)$ as soft labels to train replayed features, which allows us to utilize distillation loss [Hinton et al., 2014] for better performance.

### Table 1: Details about five datasets.

| Dataset          | Type      | #Train/#Test | #Class | #Task |
|------------------|-----------|--------------|--------|-------|
| SVHN             | Image     | 73257/26032  | 10     | 5     |
| CIFAR10          | Image     | 50000/10000  | 10     | 5     |
| CIFAR100         | Image     | 50000/10000  | 100    | 2/5/10/20 |
| THUCNews         | Text      | 50000/15000  | 10     | 5     |
| DBPedia          | Text      | 560000/70000 | 14     | 5     |

In fact, our feature replay strategy only has effects on the last FC layer which is ubiquitous in NN-based classifiers. Thus for different types of input data and NN models, GFR can be applied universally without any special modifications. However, GIR needs to design different types of generator for different data. For example, a CNN-based GAN cannot be used to generate text data. Some recent works [Wu et al., 2019; Hou et al., 2019] also improve CIL performance with some special treatments on the last FC layer. However they depend on real data replay and are perpendicular to our work.

### 4 Experiments

To evaluate our method, we conduct experiment in CIL settings, where each task corresponds to a disjoint subset of classes of the whole dataset and the classifier only has one shared output layer. Our method is called OWM+GFR.

#### 4.1 Datasets, Baselines and Model Settings

We use image datasets and two text datasets which are in detail in Table 1. To make a fair comparison, we randomly select a subset of test data as validation data and the left data are considered as test data following Hu et al. [2019]. For THUCNews/DBPedia, the size of validation dataset is 5000/10000 and for other datasets the size is 30% of the original test dataset. For CIL scenario, we split all datasets into 5 tasks and the number of class of each task is equal except DBPedia, where the 5 tasks have 3, 3, 3, 3, and 2 classes respectively. We also establish the settings of 2/10/20 tasks on CIFAR100 to further evaluate the performance of our method under different numbers of tasks.

The three image datasets we use are collected from real world and challenging for training generative model in continual learning scenario. We also choose text datasets as generating text is even harder than image as we know. We think these datasets can reflect the effectiveness of proposed method compared to existing methods.

We utilize the following baselines for comparison: 1) EWC [Kirkpatrick et al., 2017], a representiative regularization method; 2) DGR [Shin et al., 2017]: the classical GIR framework. For fair comparison, we exploit AC-GAN as generator, which is proposed in Wu et al. [2018] for image datasets. For text datasets, the generator is SseqGAN [Yu et al., 2017] which is designed for generating text. 3) Parameter Generation and Model Adaptation (PGMA) [Hu et al., 2019]: a state-of-the-art CIL method which integrates parameter generation strategy and GIR; 4) OWM [Zeng et al., 2019], the state-of-the-art subspace method which is the basis of our method. 5) OWM+GIR: The OWM baseline incorpo-
Table 2: Test accuracy after all tasks are learned. We report the mean and standard error over 5 runs with different seeds. * indicates the results taken from the original paper. † indicates p-value < 0.05 according to a two-sided t-test between the results of OWM and OWM+GFR.

![Figure 2](image-url) Figure 2: Test accuracies on all classes of already learned tasks after each task is learned in all 8 settings.

rated with GIR in which the generator is the same as in DGR baseline. We also compare with iCaRL [Rebuffi et al., 2017], a strong baseline with real data storage, to show the superiority of our method. We evaluate iCaRL with 2 sizes of storage budget: B=200 and B=2000.

We reimplement all baselines except PGMA. To make a fair comparison as much as possible, for images dataset we use classifier with the same architecture as in [Zeng et al., 2019] which has 3-layer CNN with 64, 128, 256 x x filters and 3-layer MLP with 1000 hidden units. We double the number of filters on CIFAR100. For text datasets, we use one 1D CNN layer with 1024/200 filters for THUCNews/DBPedia and the same MLP as in image datasets. We also use the same fixed pre-trained word embedding as in [Hu et al., 2019].

In our method, the generator is to generate the 1000d h and G, D are both 3-layer MLP for all datasets. In GIR, the G, D for image data have 3 deconvolution and convolution layer respectively; for text data, G is a 1-layer LSTM and D is a 1-layer 1D CNN. We make the number of parameters in G and D comparable for GIR and GFR.

4.2 Main Results
We display the final test accuracies over the whole test datasets after all tasks are learned in Table 2. The test accuracies on all learned tasks after each task is learned are also plotted in Figure 2. It should be pointed out that as the vocabulary size of DBPedia is too large to fit SeqGAN in a 1080Ti GPU with 11G memory, we cannot obtain the results of DGR and OWM+GIR on this dataset.

Table 2 shows that OWM performs much better than other existing methods, i.e. EWC, DGR and PGMA, in all settings. For relatively simple SVHN in which the images are digit numbers, DGR is almost comparable with OWM however it works much worse on CIFAR10/100 in which the images are more complex objects and THUCNews. From Figure 2 we can find after learning the second task DGR works well and on SVHN and THUCNews even better than OWM, which attributes to when training C on T2 the generator has not been trained in CL manner therefore there is no catastrophic forgetting in generator. As the number of tasks increases, DGR degrades dramatically. This phenomenon verifies that training generator continually on complex data can hardly succeed. It is worthy noticing that on CIFAR100 OWM even can improve the performance after learning T1.

We find proposed method OWM+GFR performs best in 7 of 8 settings among all methods without real data storage. Moreover, in 6 of 8 settings our method improves OWM base-
4.3 Error Analysis

In this subsection, we delve into how GFR can improve OWM’s performance. An important deficiency of OWM is that data from different tasks are never trained together so that inferring task identity is potentially hard for classifier. We expect GFR can alleviate this problem. To verify this conjecture, we first divide the final classification error into two types: Inter-Task Error and Inner-Task Error. The former conjecture, we first divide the final classification error into two types: Inter-Task Error and Inner-Task Error. The former

corresponds to task identity inference error while the latter

dominates the classification error of OWM. In 2 tasks CIFAR100 setting, too many tasks impede the training of generator thus GFR can hardly improve OWM. As displayed in Figure 2h, after training 10 tasks, the superiority of OWM+GFR to OWM almost vanishes. However, GFR is much more powerful than GIR which is applicable for the scenarios with 2-3 tasks. We will explore how to make GFR work well in the scenarios with more tasks in future work.

4.4 Visualization of Features

We visualize the generated penultimate layer features $h$ as well as the real features to further explain why GFR is effective. For real features, we randomly select 100 samples in test dataset for each class and encode them using the final feature extractor $E$. We also randomly sample 100 samples for each class from the conditional generator $G$. We project all features into a joint 2D space using t-SNE. The visualization results are in Figure 3. We only plot the features on CIFAR10 and SVHN datasets due to space limit.

Although the real features from test datasets are never seen during training by generator, we can observe a large part of generated features are clustered near some real feature clusters from the same class. Therefore, the generated features can provide useful information for classifier to adjust the decision surfaces for all classes simultaneously. We also observe some generated feature clusters, such as in grey and red, are far from corresponding real feature clusters. We find these classes are from the first or second task thus this phenomenon should attribute to the catastrophic forgetting of generator.

5 Conclusion

In this paper, we focus on class incremental learning, a challenging continual learning scenario. On the basis of OWM algorithm, we propose generate and replay the penultimate layer feature instead of input data to alleviate catastrophic forgetting of generator.
forgetting. We think this is the first successful attempt to re-
play the features of a neural network trained continually. Our
method achieves state-of-the-art performances on several im-
age and text datasets without real data storage.

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