Marginal Replay vs Conditional Replay for Continual Learning

Timothée Lesort\textsuperscript{1, 2}, Alexander Gepperth\textsuperscript{3}, Andrei Stoian\textsuperscript{2}, and David Filliat\textsuperscript{1}

\textsuperscript{1}Flowers Laboratory (ENSTA ParisTech & INRIA)
\textsuperscript{2}Thales, Theresis Laboratory
\textsuperscript{3}Fulda University

Abstract

We present a new replay-based method of continual classification learning that we term "conditional replay" which generates samples and labels together by sampling from a distribution conditioned on the class. We compare conditional replay to another replay-based continual learning paradigm (which we term "marginal replay") that generates samples independently of their class and assigns labels in a separate step. The main improvement in conditional replay is that labels for generated samples need not be inferred, which reduces the margin for error in complex continual classification learning tasks. We demonstrate the effectiveness of this approach using novel and standard benchmarks constructed from MNIST and Fashion MNIST data, and compare to the regularization-based EWC method \cite{Kirkpatrick:2016} \cite{Shin:2017}.

1 Introduction

This contribution is in the context of incremental and lifelong learning, subject that is gaining increasing recent attention \cite{Parisi:2018} \cite{Gepperth:2016}. Briefly put, the problem consists of repeatedly re-training a DNN model with new tasks (e.g., visual classes) over long time periods, while avoiding the abrupt degradation of previously learned abilities that is known under the term "catastrophic interference" or "catastrophic forgetting" \cite{Plaue:2018} \cite{French:1999} \cite{Gepperth:2016}. It has long been known that catastrophic forgetting is a problem for connectionist models \cite{French:1999} of which modern DNNs are a specialized instance, but only recently there have been efforts to propose workable solutions to this problem for deep learning models \cite{Lee:2017} \cite{Kirkpatrick:2016} \cite{RahafAljundi:2018} \cite{Kim:2018}. One aspect of the problem seems to be that gradient-based DNN training is greedy, i.e., it tries to optimize all weights in the network to solve the current task only. Previous tasks, which are not represented in the current training data, will naturally be disregarded in this process. While approaches such as \cite{Kirkpatrick:2016} \cite{Lee:2017} aim at "protecting" weights that were important for previous tasks, one can approach the problem from the other end and simply include samples from previous tasks in the training process each time a new task is introduced. This is the conditional replay approach we are proposing in this article, which is similar in spirit to \cite{Shin:2017} but presents important conceptual improvements. The major reason for performing conditional replay, and not simply using data stored from previous tasks, is that the storage of several GB of data may not be feasible for, e.g., embodied agents, or embedded devices performing object recognition, while the "essence" of previous tasks, in the form of DNN weights, usually requires far less space. A downside of this and similar approaches is that the time complexity of adapting to a new task is not constant but depends on the number of preceding tasks that should be "remembered". Or, conversely, if continual learning should be performed at constant time complexity, only a fixed amount of samples can be generated, and thus there will be forgetting, although it won't be catastrophic.
1.1 Contribution

The original contributions of this article can be summarized as follows: first of all, we propose conditional replay as a method for continual classification learning, and compare conditional and marginal replay models on a common set of benchmarks. We furthermore propose an improvement of marginal replay as proposed in (Shin et al., 2017) by using GANs. To measure the merit of these proposals, we use two experimental settings that have not been previously considered for benchmarking generative replay: rotations and permutations. Finally, we show the principled advantage that generative replay techniques have with respect to regularization methods like EWC in a "one class per task" setting, which is after all a very common setting in practice and in which discriminatively trained models strongly tend to assign the same class label to every sample regardless of content.

1.2 Related work

The field of incremental learning is growing and has been recently reviewed in, e.g., (Parisi et al., 2018; Gepperth and Hammer, 2016). In the context of neural networks, principal recent approaches include ensemble methods (Ren et al., 2017; Fernando et al., 2017), regularization approaches (Kirkpatrick et al., 2016; Lee et al., 2017; Rahaf Aljundi and Tuytelaars, 2018; Kim et al., 2018; Srivastava et al., 2013; Hinton et al., 2012), dual-memory systems (Kemker and Kan, 2017; Rebuffi et al., 2017; Gepperth and Karaoguz, 2015) and generative replay methods. In the context of “pure” DNN methods, regularization approaches are predominant: whereas it was proposed in (Goodfellow et al., 2013) that the popular Dropout regularization can alleviate catastrophic forgetting, the EWC method (Kirkpatrick et al., 2016) proposes to add a term to the DNN energy function that protects weights that are deemed to be important for the previous sub-task(s). Whether a weight is important or not is determined by approximating and analyzing the Fisher information matrix of the DNN. A somewhat related approach is pursued with the incremental moment matching (IMM, see (Lee et al., 2017)) technique, where weights are transferred between DNNs trained on successive sub-tasks by regularization techniques, and the Fisher information matrix is used to "merge" weights for current and past sub-tasks. Other regularization-oriented approaches are proposed in (Rahaf Aljundi and Tuytelaars, 2018; Srivastava et al., 2013) which focus on enforcing sparsity of neural activities by lateral interactions within a layer, or in (Kim et al., 2018). Concerning recent advances in generative replay improving upon (Shin et al., 2017): (Wu et al., 2018; Anonymous, 2019) propose a conditional replay mechanism similar to the one investigated here, but their goal is the sequential learning of data generation and not classification tasks.

2 Methods

A basic notion in this article is that of a continual learning task (CLT), denoting a classification problem that is composed of two or more sub-tasks which are presented sequentially to the model in question. Here, the CLTs are constructed from two standard visual classification benchmarks: MNIST and Fashion MNIST, either by dividing available classes into several sub-tasks, or by performing per-sample image processing operations that are identical within, and different between, sub-tasks. All continual learning models are then trained and evaluated in an identical fashion on all CLTs, and performances are compared by a simple visual inspection of classification accuracy plots.

2.1 Benchmarks

MNIST (LeCun et al., 1998) is a common benchmark for computer vision systems and classification problems. It consists of gray scale images of handwritten digits (0-9).

Fashion MNIST (Xiao et al., 2017) consists of clothes images and is structured like the standard MNIST dataset. We choose this dataset because it claims to be a “more challenging classification task than the simple MNIST digits data (Xiao et al., 2017)” while having the same data dimensions, number of classes and roughly the same number of samples.
2.2 Continual learning tasks (CLTs)

Rotations New sub-tasks are generated by choosing a random rotation angle $\beta \in [0, \pi/2]$ and then performing a 2D in-plane rotation on all samples of the original benchmark. As both benchmarks we use contain samples of 28x28 pixels, no information loss is introduced by this procedure. We limit rotation angles to $\pi/2$ because larger rotations could mix MNIST classes like 0 and 9.

Permutations New sub-tasks are generated by defining a random pixel permutation scheme, and then applying it to each data sample of the original benchmark.

Disjoint classes For each benchmark, this CLT has as many sub-tasks as there are classes in the benchmark (10 in this article). Each sub-task contains all the samples of a single class. As the classes are balanced for both benchmarks we use, this does not unduly favor certain classes.

2.3 Models

Fully-connected network As a reference implementation, we use a fully-connected network (2 hidden layers with 200 neurons each) with ReLU activation function. No batch normalization or dropout is performed. All other training parameters are described in Appendix B.

EWC We re-implemented the algorithm described in (Kirkpatrick et al., 2016), choosing two hidden layers with 200 neurons each.

Marginal replay In the context of classification, the marginal replay (Anonymous, 2019; Shin et al., 2017; Wu et al., 2018) method works as follows: For each sub-task $t$, there is a dataset $D_t$, a classifier $C_t$, a generator $G_t$, and a memory of past samples composed of a generator $G_{t-1}$ and a classifier $C_{t-1}$. The latter two allow the generation of artificial samples $D_{t-1}$ from previous sub-tasks. Then, by training $C_t$ and $G_t$ on $D_t$ and $D_{t-1}$, the model can learn the new sub-task without forgetting old ones. At the end of the sub-task, $C_t$ and $G_t$ are frozen and replace $C_{t-1}$ and $G_{t-1}$. In our experiments, we always train in a way that makes samples balanced between current sub-task $D_t$ and past sub-tasks $D_{t-1}$. We choose to evaluate two different models: WGAN_GP as used in (Shin et al., 2017) and the original GAN model (Goodfellow et al., 2014) since it is a competitive baseline (Lesort et al., 2018).

Conditional replay The conditional replay method is derived from marginal replay: instead of saving a classifier and a generator, the algorithm only saves a generator that can generate conditionally (for a certain class). Hence, for each sub-task $t$, there is a dataset $D_t$, a classifier $C_t$ and two generators $G_t$ and $G_{t-1}$. The goal of $G_{t-1}$ is to generate data from all the previous sub-tasks during training on the new sub-task. Since data is generated conditionally, samples automatically have a label and thus do not require a frozen classifier. $C_t$ and $G_t$ learn from generated data $D_{t-1}$ and $D_t$. At the end of a sub-task $t$, $C_t$ is able to classify data from the current and previous sub-tasks, and $G_t$ is able to sample from them also. We choose to use two different popular conditional models: CGAN described in (Mirza and Osindero, 2014) and CVAE (Sohn et al., 2015).

3 Results and discussion

As can be observed from Fig. 1, the methods we propose (marginal replay with GAN, conditional replay with CGAN and conditional replay with CVAE) outperform all others, on all CLTs, by quite some margin. In particular, in our experiments, the clear advantage of those methods over marginal replay with WGAN-GP is the higher stability of the generative models. This is not only observable in Fig. 1 but also when measuring performance on the first sub-task only during the course of continual learning (see Fig. 8) as well as computing the Fréchet Inception Distance (FID, see Fig. 9). Fig. 7 additionally confirms what Fig. 1 suggests implicitly: that the generator learns incrementally over time, balancing its stability and plasticity in a smooth way. For completeness, we verified that the manner of balancing the number of generated and new samples has a huge impact, so care needs to be taken here (see Fig. 2). Conditional replay is less sensitive to the balance of data than marginal replay since it can make a clear distinction between data from different classes. Balance task necessitate to generate a lot of samples from past tasks which consequently increases the learning time gradually. Conditional replay is then a good solution to learn with less generated data and then reduce training time.

3
Particular attention should be given to the performance of EWC: while generally acceptable for rotation and permutation CLTs, it completely fails for the disjoint CLT. This is due to the fact that there is only one class in each sub-task, making EWC try to map all samples to the currently presented class label regardless of input, since no replay is available to include samples from previous sub-tasks.

![Accuracy for MNIST Disjoint CLT](image1.png)

(a) accuracy for MNIST disjoint CLT

![Accuracy for Fashion MNIST Disjoint CLT](image2.png)

(b) accuracy for Fashion MNIST disjoint CLT

![Accuracy for MNIST Permutation CLT](image3.png)

(c) accuracy for MNIST permutation CLT

![Accuracy for Fashion MNIST Permutation CLT](image4.png)

(d) accuracy for Fashion MNIST permutation CLT

![Accuracy for MNIST Rotation CLT](image5.png)

(e) accuracy for MNIST rotation CLT

![Accuracy for Fashion MNIST Rotation CLT](image6.png)

(f) accuracy for Fashion MNIST rotation CLT

Figure 1: Test set accuracies during training on different CLTs, shown for all sub-tasks (indicated by dotted lines).

## 4 Conclusion

We have proposed two novel ways of performing continual learning with replay-based models and empirically demonstrated (on novel benchmarks) their merit w.r.t. the state of the art. Clearly, focus of future research will lie on understanding the current shortcomings of conditional replay methods and removing them, thus providing a replay-based method of greater simplicity, elegance and learning capacity. Furthermore, we will investigate the advantage of conditional replay with less generated data.
References

Anonymous. 2019. Generative Models from the perspective of Continual Learning. In Submitted to International Conference on Learning Representations. https://openreview.net/forum?id=SleFtj0cKQ under review.

Chrisantha Fernando, Dylan Banarse, Charles Blundell, Yori Zwols, David Ha, Andrei A Rusu, Alexander Pritzel, and Daan Wierstra. 2017. Pathnet: Evolution channels gradient descent in super neural networks. arXiv preprint arXiv:1701.08734 (2017).

RM French. 1999. Catastrophic forgetting in connectionist networks. Trends in Cognitive Sciences 4 (1999).

Alexander Gepperth and Barbara Hammer. 2016. Incremental learning algorithms and applications. In European Symposium on Artificial Neural Networks (ESANN).

A Gepperth and C Karaoguz. 2015. A bio-inspired incremental learning architecture for applied perceptual problems. Cognitive Computation (2015). accepted.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In Advances in Neural Information Processing Systems 27, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger (Eds.), Curran Associates, Inc., 2672–2680. http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf

Ian J. Goodfellow, Mehdi Mirza, Da Xiao, Aaron Courville, and Yoshua Bengio. 2013. An Empirical Investigation of Catastrophic Forgetting in Gradient-Based Neural Networks. (2013). https://doi.org/10.1088/1751-8113/44/8/085201 arXiv:1312.6211

Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan R. Salakhutdinov. 2012. Improving neural networks by preventing co-adaptation of feature detectors. (2012), 1–18. https://doi.org/10.1023/A:1011801310899

Ronald Kemker and Christopher Kanan. 2017. Fearnet: Brain-inspired model for incremental learning. arXiv preprint arXiv:1711.10563 (2017).

Hyo-Eun Kim, Seungwook Kim, and Jaehwan Lee. 2018. Keep and Learn: Continual Learning by Constraining the Latent Space for Knowledge Preservation in Neural Networks. CoRR abs/1805.10784 (2018). arXiv:1805.10784 http://arxiv.org/abs/1805.10784

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell. 2016. Overcoming catastrophic forgetting in neural networks. (2016). https://doi.org/10.1073/pnas.1611835114 arXiv:1612.00796

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. 1998. Gradient-Based Learning Applied to Document Recognition. (1998). http://ieeexplore.ieee.org/document/726791/

Sang-Woo Lee, Jin-Hwa Kim, Jaehyun Jun, Jung-Woo Ha, and Byoung-Tak Zhang. 2017. Overcoming catastrophic forgetting by incremental moment matching. In Advances in Neural Information Processing Systems. 4655–4665.

Timothée Lesort, Jean-François Goudou, and David Filliat. 2018. Training Discriminative Models to Evaluate Generative Ones. arXiv preprint arXiv:1806.10840 (2018).

Mehdi Mirza and Simon Osindero. 2014. Conditional Generative Adversarial Nets. (2014). arXiv:cs.LG/1411.1784

German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. 2018. Continual Lifelong Learning with Neural Networks: A Review. arXiv preprint arXiv:1802.07569 (2018).

B Pfülb, A Gepperth, S Abdullah, and A Krawczyk. 2018. Catastrophic forgetting: still a problem for DNNs. In International Conference on Artificial Neural Networks (ICANN).
Marcus Rohrbach Rahaf Aljundi and Tinne Tuytelaars. 2018. Selfless Sequential Learning. CoRR abs/1806.05421 (2018). [http://arxiv.org/abs/1806.05421](http://arxiv.org/abs/1806.05421)

Sylvestre-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. 2017. icarl: Incremental classifier and representation learning. In Proc. CVPR.

Boya Ren, Hongzhi Wang, Jianzhong Li, and Hong Gao. 2017. Life-long learning based on dynamic combination model. Applied Soft Computing 56 (2017), 398–404.

Hanul Shin, Jung Kwon Lee, Jaehong Kim, and Jiwon Kim. 2017. Continual learning with deep generative replay. In Advances in Neural Information Processing Systems. 2990–2999.

Kihyuk Sohn, Honglak Lee, and Xinchen Yan. 2015. Learning Structured Output Representation using Deep Conditional Generative Models. In Advances in Neural Information Processing Systems 28, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett (Eds.). Curran Associates, Inc., 3483–3491. [http://papers.nips.cc/paper/5775-learning-structured-output-representation-using-deep-conditional-generative-models.pdf](http://papers.nips.cc/paper/5775-learning-structured-output-representation-using-deep-conditional-generative-models.pdf)

Rupesh Kumar Srivastava, Jonathan Masci, Sohrob Kazerounian, Faustino Gomez, and Jürgen Schmidhuber. 2013. Compete to Compute. Nips (2013), 2310–2318.

Chenshen Wu, Luis Herranz, Xiaolei Liu, Yaxing Wang, Joost van de Weijer, and Bogdan Raducanu. 2018. Memory Replay GANs: learning to generate images from new categories without forgetting. arXiv preprint arXiv:1809.02058 (2018).

Han Xiao, Kashif Rasul, and Roland Vollgraf. 2017. Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms. (2017), 1–6. arXiv:1708.07747 [http://arxiv.org/abs/1708.07747](http://arxiv.org/abs/1708.07747)
A Task Balance Influence

Figure 2: We compare accuracy on first task when the ratio between size of old task and new task is 1 (balanced) or 1/5 (unbalanced, factor was chosen empirically).

B Hyper-parameters

Table 1: Hyperparameters for MNIST and Fashion MNIST all models (all CL settings have the same training hyper parameters with Adam)

| Method           | Epochs | LR Classifier | LR Generator | beta1 | beta2  | Batch Size |
|------------------|--------|---------------|--------------|-------|--------|------------|
| Marginal Replay  | 25     | 0.01          | 2e-4         | 5e-1  | 0.999  | 64         |
| Conditional Replay| 25    | 0.01          | 2e-4         | 5e-1  | 0.999  | 64         |
| Ewc              | 25     | 0.01          | -            | 5e-1  | 0.999  | 64         |
| Finetuning       | 25     | 0.01          | -            | 5e-1  | 0.999  | 64         |
| Expert           | 50     | 0.01          | -            | 5e-1  | 0.999  | 64         |
C Data

C.1 CLT: Disjoint

Figure 3: MNIST training data for the disjoint CLT
C.2 CLT: rotations

Figure 4: MNIST training data for rotation sub-tasks.

Figure 5: MNIST training data for permutation-type CLTs.
C.3 CLT: permutations

Figure 6: Visualization of training data for the MNIST permutation CLT. The number of rows and columns corresponds to the number of sub-tasks, here: 5. In each raw, from left to right, we display the same selected set of samples from each sub-task in a rectangular area. In each line, the inverse transformation from the corresponding sub-task to the original data is applied, thus making data from a different sub-task interpretable in each line. This figure should be viewed together with Fig.7.
D Generated data

Figure 7: Visualization of data generated during training of marginal replay + GAN on the MNIST permutation CLT. The number of rows and columns corresponds to the number of sub-tasks, here: 5, In each line, from left to right, we display a selected set of samples generated after training on each sub-task in a rectangular area. In each raw, the inverse transformation from the corresponding sub-task to the original data is applied, thus making generated data from a different sub-task interpretable in each line. We observe stable retention behavior as the number of sub-tasks increases, while data from new sub-task is learned successfully as well.
E Accuracy on first sub-task

Figure 8: Comparison of the accuracy of each approach on the first sub-task. This is another, very intuitive measure of how much is forgotten during continual learning. Means and standard deviations computed over 8 seeds.
Figure 9: Comparison of the Fréchet Inception Distance (FID) between generated samples and test set samples for all replay-based methods (lower is better). Abrupt growth of the FID is symptomatic of a divergence in the generator and the generation of samples completely alien to the dataset.