COLLABORATIVE METHOD FOR INCREMENTAL LEARNING ON CLASSIFICATION AND GENERATION

Byungju Kim, Jaeyoung Lee, Kyungsu Kim, Sungjin Kim and Junmo Kim*

Department of Electric Engineering, KAIST, South Korea
Samsung Research

ABSTRACT

Although well-trained deep neural networks have shown remarkable performance on numerous tasks, they rapidly forget what they have learned as soon as they begin to learn with additional data with the previous data stop being provided. In this paper, we introduce a novel algorithm, Incremental Class Learning with Attribute Sharing (ICLAS), for incremental class learning with deep neural networks. As one of its component, we also introduce a generative model, incGAN, which can generate images with increased variety compared with the training data. Under challenging environment of data deficiency, ICLAS incrementally trains classification and the generation networks. Since ICLAS trains both networks, our algorithm can perform multiple times of incremental class learning. The experiments on MNIST dataset demonstrate the advantages of our algorithm.

Index Terms— Incremental Learning, Deep Neural Networks, Generative Adversarial Networks

1. INTRODUCTION

Human intelligence has been always a target of artificial intelligence for comparison. With the huge data provided, DNN has achieved performance level beyond that of the human brain can achieve [1]. However, there is still a gap between artificial intelligence and human intelligence in terms of learning capability. To train an algorithm, including DNN, it is commonly assumed that the entire training dataset is accessible throughout the training sequence. Under this assumption, most existing algorithms can be trained thoroughly with proper optimization techniques. Human, however, learns differently. A common learning environment for a human is rather an environment with a stream of small data. The entire data does not have to be provided all at once. Too much data rather disturbs the learning process. The maximum number of recognizable objects is neither defined from the beginning. We are able to recognize an increasing number of objects by learning incrementally through time.

To resolve the gap, an algorithm should be able to learn incrementally. Here, we focus on training a classification network to recognize additional classes. More precisely, we assume two properties as follows:

- For each class incremental situation, we provide a set of image-label pairs of the new classes that are not previously provided.
- Network should predict the class label by single output layer.

The first property implies that previously provided data is not accessible during the incremental situation. It degrades the performance rapidly; this phenomenon is known as catastrophic forgetting [2] in the literature. Although these properties are important features that discriminate artificial intelligence from human, only a few research has been conducted to overcome this issue.

In this paper, we introduce Incremental Class Learning with Attribute Sharing, (ICLAS), a DNN-based incremental learning algorithm for image classification and generation. The ICLAS collaboratively trains a generative model and a classifier. As a generative model, we introduce incremental GAN (incGAN), which is designed to effectively assist the classifier to learn additional classes. Other than the incremental trainability, incGAN is able to generate images with more variability than the training images through attribute sharing. It extracts class-independent attributes from training images, and generates new images of a designated class with those attributes.

2. RELATED WORKS

Catastrophic forgetting. The problem of catastrophic forgetting [3], which loses information about previously learned task while learning a new task, has been issued with many artificial neural networks. To avoid this problem, the basic approach is to build a new network for the new task and transfer the parameters of the previously learned task to share the mid-level representation [4, 5, 6] or the decision boundaries [7]. As a branch of approaches to catastrophic forgetting problem, Generative Replay (GR) has been proposed [8]. It transfers the knowledge by replaying the old tasks.

Memory-based approaches with regularization have also been proposed. By efficient use of an episodic memory, which stores a subset of the observed examples, iCaRL [9] uses a nearest-mean-of-exemplars classification strategy and GEM [10] makes inequality constraints to minimize the negative backward transfer. LwF [11] is related to these approaches, but stores the pseudo-labels, which is the output of the old
tasks for new training data. EWC \cite{1}, inspired by the synap-
tic consolidation of the brain, uses a synaptic memory to store
the weights. This approach selectively reduces the learning
rate for the important synaptic weights on previously learned
task by using a soft, quadratic constraint.

**Generative Adversarial Networks.** Generative Adversarial
Networks (GANs) \cite{22} is one of the most important successes
on the image generation task. The main idea of GANs is to
have two competing networks models: discriminator (D) and
generator (G). After the GANs, a lot of new research based
on GANs has been carried out and dramatically improved the
performance of the generative models. As a representative
example, VAE-GAN \cite{13} is a GANs model combined with
the variational autoencoder (VAE) \cite{14} to use learned repre-
sentations by modifying the reconstruction objective of VAE.
Instead of the pixel-wise reconstruction error in VAE, VAE-
GAN is trained with adversarial loss. CVAE-GAN \cite{15}, a
variant of VAE-GAN, is a model which combines conditional
variational autoencoder (CVAE) \cite{16} with GANs. We used
CVAE-GAN as our baseline structure for incGAN.

**3. INCREMENTAL LEARNING WITH ATTRIBUTE
SHARING**

In this paper, we aim to solve an incremental class learning.
Formally, we define an incremental class stage \( S_i \), as the \( i \)-th
phase in which new classes come in. A sequence of incremental
learning consists of each stage. At each stage \( S_i \), a
set of images \( X^i \) and the corresponding labels \( Y^i \) are pro-
vided. Each image \( x_k^i \in X^i \) has its ground truth class label
\( y^i_{mk} \in C^i \), where \( C^i \) is a set of class labels of provided data
\( X^i \). Every two different sets, \( C^i \) and \( C^j \) are disjoint. At each
stage \( S_i \), we incrementally train a classifier, so that the classi-
fier can additionally recognize images, which belong to new
classes \( c \in C^i \). We subsequently train a generator \( G \), and
a discriminator \( D \), so that they can additionally generate and
discriminate images of class \( C^i \), respectively.

Major challenge of incremental class learning is the ab-

cence of former data, \( \bigcup_{k=0}^{i-1} X^k \). In the literature \cite{2} the

it is known that the absence of former data can cause the
catastrophic forgetting problem on neural network. How-

ever, recent improvement of generative model shows that the

high-quality fake data can be generated with properly trained

networks. Using generative models, we can generate images
with their labels of \( \bigcup_{k=0}^{i-1} C^k \), so that we can simply resolve the

incremental class learning problem by fine-tuning the
classifier, \( f(x) \).

If the classifier is the only network we train incrementally,
the generative model would not able to generate images of \( \bigcap_{k=0}^{i-1} C^k \)

of new classes in \( C^i \). Therefore, at stage \( S_i^{i+1} \), we cannot gen-

erate the images of \( C^i \) from the generator, and the classifier

would forget the knowledge on \( C^i \). To make ICLAS multiple
time solution, the generative model should also be increment-
tially trained to generate the images of \( C^i \) while preventing the

forgetting problem.

**Generative Model for Incremental Class Learning** Here, we
introduce our generative model, incremental GAN (inc-
GAN), designed for incremental class learning. The overall
architecture of proposed incGAN is illustrated in Figure 1.

Our generative model is a variant of CVAE-GAN \cite{16} \cite{15}

which can generate an image with class conditioning. It takes
an image and a target class as its input, and outputs an im-
age. Once the encoder extracts the attribute from the input
image, decoder generates the output image of the target class.

Although the discriminator network is omitted from Figure 1,
the generator network, which is composed of encoder and de-
coder, is trained adversarially against the discriminator net-
work.

Most of generative models have mainly focused on gener-
ating realistic images with high variability which is de-

rived from various types of noise. On the other hand, inc-
GAN only focus on generating realistic images, while regu-

lating the variability from noise with attribute preservation

loss. Since the encoder network of incGAN does not take
class label as its input, it can extract the attribute from the
image class-independently. Therefore, incGAN learns single
attribute space over the entire data, and the attribute space is
applicable for every classes by the decoder network. It en-
ables the generated images to share the attributes across the
stages and helps the classifier to concentrate on the class dif-
ference not on the attribute. Due to this attribute sharing, in-
cGAN can generate images with even higher variability then
training images.

To constrain the extracted attribute class-independent, we
add an auxiliary classification loss, \( L_{aux} \). Taking the attribute
vector, \( Enc(x) \), as its input, the auxiliary classification net-
work is composed of gradient reversal layer (GRL) \cite{18},
followed by a fully-connected layer, which tries to predict the
label of \( x \). The error signal derived from the auxiliary clas-
sification network adversarially trains the encoder network,
so that it will be difficult to predict class label by observ-
ing \( Enc(x) \). This results in extraction of class-independent
attributes \( Enc(x) \). Due to its class-independence, an attri-

bute which appears in later stage can be adopted to for-

merly learned classes; all generated images share the attribute
space. The attribute sharing loss is defined as:

\[
L_{share} = L_{aux} + L_{attr} = L_{aux} + \| Enc(x^i_k) - Enc(G(x^i_k, c)) \|_2, \tag{1}
\]

where \( Enc(\cdot) \) and \( G(\cdot, \cdot) \) are encoder and generator functions,
and \( c \) is an arbitrary class condition for the generator. Note
that the generator function \( G(x^i_k, c) \) is a composition of encoder
and decoder function, i.e., \( G(x^i_k, c) = Dec(Enc(x^i_k), c) \).

**Knowledge Distillation from Classifier** Here, we describe
our algorithm training generator incrementally with the
trained classifier in the loop to make ICLAS multiple time
solution. At the moment of training incGAN, the classifier
Fig. 1. Overall architecture of incGAN model. The encoder network (red) extracts an attribute vector from given query image. Then, with arbitrary target class, the decoder network (green) generates an image of the target class. The parameter-shared encoder (bottom right) constrains the query image and the generated image to have same attribute. Note that discriminator network of our incGAN is omitted in the figure.

is already trained to recognize images of $C_i$. Therefore, we can distill the knowledge of classifier to train incGAN. Once the discriminator can recognize real and generated images, the generator can also be trained adversarially for new classes. Therefore, it is sufficient to train the discriminator to recognize real and fake images of new classes. We first generate realistic images of each class. Since the images are generated with class conditions, we can generate image-label pairs for $\bigcup_{k=0}^{i-1} C^k$ with given training data $X^i$. Then we train the discriminator treating the remaining images as real images for $\bigcup_{k=0}^{i-1} C^k$. However, without any additional constraints, the performance has been degraded by consecutive incremental class learning.

To distill the knowledge of the classifier, we define a score vector, $s^i(x)$, by concatenating outputs of discriminator from different conditions:

$$ s^i(x) = \begin{pmatrix} D^i(x, c = 0) \\ D^i(x, c = 1) \\ \vdots \\ D^i(x, c = N^i - 1) \end{pmatrix}, $$

where $D^i(\cdot, \cdot)$ is the discriminator output at $S^i$ with given image and class, and $N^i$ is the number of total classes to generate, i.e., $N^i = \sum_{k=0}^{i} |C^k|$. Then, $L_{\text{distill}}$ is defined as follows:

$$ L_{\text{distill}} = H(softmax(f(x), s^i(x))), $$

where $H(\cdot, \cdot)$ denotes cross-entropy function, and $f(x)$, which is probability vector from trained classifier, plays role of label.

The $L_{\text{distill}}$ represents the idea of “selecting the best fit class for the given fake image”. Without the $L_{\text{distill}}$ term, the discriminator of incGAN would be trained toward a direction which makes $D^i(G^i(x), \cdot)$ to zero (fake image), regardless of correlation between the generated image and the given class label. By addition of $L_{\text{distill}}$, the discriminator of incGAN is now able to recognize the input image even if it is a fake image.

To sum up, the overall loss $L_{\text{incGAN}}$ to train incGAN incrementally is a weighted sum of VAE-GAN, attribute preservation loss, and distillation loss:

$$ L_{\text{incGAN}} = L_{\text{VAE-GAN}} + \lambda_1L_{\text{share}} + \lambda_2L_{\text{distill}}, $$

where $\lambda_1$ and $\lambda_2$ are the hyperparameters that balance the loss terms. The generator is trained consecutively after the classifier has been trained incrementally. While the generator learns new classes, it also learns new attributes. The collaborative learning between the two networks, the classifier and incGAN, prevents the forgetting problem from deficient data.

4. EXPERIMENTAL RESULT

In this section, we demonstrate the experimental results of ICLAS. We have conducted experiments on MNIST [19] dataset. We follow the experimental setting in [8], for incremental class learning. Ten digit categories are partitioned into five mutually exclusive sets: $C^0 = \{0, 1\}$, $C^1 = \{2, 3\}$, $C^2 = \{4, 5\}$, $C^3 = \{6, 7\}$, and $C^4 = \{8, 9\}$. Naturally, the provided data $X^i$s at each stage $S^i$ are also mutually exclusive. For evaluation at $S^i$, the classifier categorizes the input images into one of $\bigcup_{k=0}^{i} C^k$. Therefore, the classification network should learn not only how to categorize $X^i$ into one of $C^i$, but also how to differentiate $X^i$ from the images which it had trained with.

At the beginning of each incremental stage, the provided images are unseen for both classifier and incGAN. In other words, incGAN should generate images from query images of unseen classes. Therefore, the superior performance of ICLAS implies that the encoder network of incGAN is able
Fig. 2. Generated images by incGAN during the incremental class learning. The images in the same row are generated with same target class. Through the sequence of incremental learning, incGAN learns how to generate the additional classes. After multiple times of incremental learning, incGAN still preserves the attribute of query image. In the red box, the generated images are very noisy because incGAN is not yet trained for corresponding classes.

Fig. 3. Classification performance comparison with other methods. In each stage, the accuracy is evaluated over all provided class up to the stage.

to extract attributes from images of unseen classes. Moreover, if the attributes are class-dependent, the attribute vector from unseen image would be noisy, and noisy attribute would cause degradation on generated images.

Figure 3 presents classification performance at each stage. As soon as we start providing $X^i$ while stop providing $X^{i-1}$, the network would be rapidly saturated to $C^i$, and forget formerly trained categories completely. In Figure 3, performance marked as SGD, stochastic gradient descent, shows how rapidly the network forgets with conventional training algorithm. Figure 3 also shows that the network trained with ICLAS, can clearly recognize every classes they have learned. It also illustrates performance from other incremental approaches. The performance of ICLAS is superior to other incremental approaches. Although the approaches vary in their detailed architectures and experimental settings, they consistently aim to solve the forgetting problem. Under our experimental setting, LwF and EWC methods suffer from explosive growth of the scales of parameters on the last layer, connected to $C^i$. To prevent the forgetting by scale explosion, we normalize the last layer for LwF and EWC methods. Otherwise, they completely forget the knowledge learned from former stages.

Figure 2 illustrates that the generator have successfully learned new classes. At each stage $S^i$, we have selected a query image from each class in $C^i$, and generates images for all classes. Note that incGAN preserves the attribute of query image while it generates an image of formerly learned classes. Since $L_{share}$ constrains incGAN to preserve the attributes and share the attribute space, incGAN can learn sequentially without losing its nature of attribute preservation. By attribute sharing, the attribute vector extracted from images of $C^i$ represents same meaning for classes of other stages; Images in same column have same attribute in Figure 2. The noisy images in red box of Figure 2 are the generated images with untrained class label in the stage. As the incremental learning progresses, Figure 2 shows that incGAN can generate the images of additional classes.

5. CONCLUSION

In this paper, we introduce a training algorithm, ICLAS, for incremental class learning under data-deficient environment. To prevent the forgetting problem of neural network-based image classification, we introduce a novel generative model, incGAN, which emulates the attributes from the input image. We propose a novel approach that distills the knowledge of classification networks to train the generative model incrementally. Our algorithm resembles human in that they recall previous knowledge to learn new knowledge. In this respect, we expect our algorithm leads the artificial intelligence one step forward to human intelligence.

Acknowledgement This research was supported by Samsung Research.
6. REFERENCES

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[2] James Kirkpatrick, Razvan Pascanu, Neil C. Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieska Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell, “Overcoming catastrophic forgetting in neural networks,” CoRR, vol. abs/1612.00796, 2016.

[3] Michael McCloskey and Neal J Cohen, “Catastrophic interference in connectionist networks: The sequential learning problem,” Psychology of learning and motivation, vol. 24, pp. 109–165, 1989.

[4] Maxime Oquab, Leon Bottou, Ivan Laptev, and Josef Sivic, “Learning and transferring mid-level image representations using convolutional neural networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 1717–1724.

[5] Wang Xiong, Yijie Wang, and Li Cheng, “Fisher discriminant analysis random forest for online class incremental learning,” in 2018 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Ubiquitous Computing & Communications, Big Data & Cloud Computing, Social Computing & Networking, Sustainable Computing & Communications (ISPA/IUCC/BDCloud/SocialCom/SustainCom). IEEE, 2018, pp. 597–604.

[6] Juntong Zhang, Jie Zhang, Shalini Ghosh, Dawei Li, Serafettin Tasci, Larry P. Heck, Hemin Zhang, and C.-C. Jay Kuo, “Class-incremental learning via deep model consolidation,” CoRR, vol. abs/1903.07864, 2019.

[7] Heechul Jung, Jeongwoo Ju, Minju Jung, and Junmo Kim, “Less-forgetting learning in deep neural networks,” CoRR, vol. abs/1607.00122, 2016.

[8] Hanul Shin, Jung Kwon Lee, Jaehong Kim, and Jiwon Kim, “Continual learning with deep generative replay,” CoRR, vol. abs/1705.08690, 2017.

[9] Sylvester-Alvise Rebuffi, Alexander Kolesnikov, and Christoph H. Lampert, “icarl: Incremental classifier and representation learning,” CoRR, vol. abs/1611.07725, 2016.

[10] David Lopez-Paz and Marc’Aurelio Ranzato, “Gradient episodic memory for continuum learning,” CoRR, vol. abs/1706.08840, 2017.

[11] Zhizhong Li and Derek Hoiem, “Learning without forgetting,” in European Conference on Computer Vision. Springer, 2016, pp. 614–629.

[12] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, 2014, pp. 2672–2680.

[13] Anders Boesen Lindbo Larsen, Søren Kaae Sønderby, Hugo Larochelle, and Ole Winther, “Autoencoding beyond pixels using a learned similarity metric,” arXiv preprint arXiv:1512.09300, 2015.

[14] Diederik P Kingma and Max Welling, “Auto-encoding variational bayes,” arXiv preprint arXiv:1312.6114, 2013.

[15] Jianmin Bao, Dong Chen, Fang Wen, Houqiang Li, and Gang Hua, “CVAE-GAN: fine-grained image generation through asymmetric training,” CoRR, vol. abs/1703.10155, 2017.

[16] Kihyuk Sohn, Honglak Lee, and Xinchen Yan, “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., pp. 3483–3491. Curran Associates, Inc., 2015.

[17] Ari Seff, Alex Beatson, Daniel Suo, and Han Liu, “Continual learning in generative adversarial nets,” CoRR, vol. abs/1705.08395, 2017.

[18] Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky, “Domain-adversarial training of neural networks,” Journal of Machine Learning Research, vol. 17, no. 59, pp. 1–35, 2016.

[19] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner, “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.