Lifelong Learning Strategy: Self-Memory Supervising and Dynamically Growing Process

Youcheng Huang  Chenwei Tang  Jundong Zhou  Chunxin Yang

Abstract
From childhood to youth, human gradually come to know the world. But for neural networks, this growing process seems difficult. Trapped in catastrophic forgetting, current researchers feed data of all categories to a neural network which remains the same structure in the whole training process. We compare this training process with human learning patterns, and find two major conflicts. In this paper, we study how to solve these conflicts on generative models based on the conditional variational autoencoder (CV AE) model. To solve the uncontinuous conflict, we apply memory playback strategy to maintain the model’s recognizing and generating ability on invisible used categories. And we extend the traditional one-way CV AE to a circulatory mode to better accomplish memory playback strategy. To solve the ‘dead’ structure conflict, we rewrite the CV AE formula then are able to make a novel interpretation about the functions of different parts in CV AE models. Based on the new understanding, we find ways to dynamically extend the network structure when training on new categories. We verify the effectiveness of our methods on MNIST and Fashion MNIST and display some very insteresting results.

1. Introduction
Since childhood, humans have been constantly learning to recognize the world, to make new memories and to recognize new objects. Humans take this continual learning ability for granted, but it is difficult for current deep learning models to do so. Trapped in catastrophic forgetting, most current development classification and generation methods require a carefully designed model that huge enough to learn all categories’ knowledges before the training start, and to feed data with all categories with the model. These kind of models and training process have two major conflicts when comparing to human learning patterns:

- **Uncontinuous conflict:** when new objects emerge, human gradually learn new knowledges. However, deep learning models learn knowledges in a label-limited object sets.

- **‘Dead’ structure conflict:** with intelligence developing, neurons in human brains gradually change themselves and become richer. However, deep learning models have ‘dead’ stuctures staying the same.

These two conflicts make current deep learning methods less intelligent.

In the continual learning process, the researchers will feed sequential data ordered in categories to train the model, and keep already used categories unavailable as the training process goes on. Catastrophic forgetting is when, without any contraint, the model will no longer hold the knowledges about previous categories (McCloskey & Cohen, 1989) when it is training on a new category. Note that the image generation tasks are more complex and general than classification tasks. This paper discusses to continually train generation models. More specifically, the continual training of label-conditioned self-encoding models. We pick up conditional variational autoencoder (CV AE) (Sohn et al., 2015) because it is simple, not explored yet and has meaningful mathematical formulas. According to the categories order, we gradually feed each category to train a CV AE network in which applying the self-memory supervision and circulatory mode to solve the first conflict and equipping CV AE with dynamically growing structure to solve the second conflict. Finally, the network can generate corresponding data through Gaussian noises and condition inputs.

About the open problem of continual learning, recent researchers seek for breakthoughs from two aspects. One is to find better directions of optimizing parameters (Kirkpatrick et al., 2017) (Titsias et al., 2019) (Nguyen et al., 2017) (Cao, 2019) and the other is based on memory playback (Wu et al., 2018) (Seff et al., 2017) or knowledge distillation methods (Zhai et al., 2019). The researches focused on parameter optimization have made a deep investigation on the mathematical properties of neural networks. Parameter regularization (Seff et al., 2017) can partly solve the problem of continually training discrimination and generation models, while poor performance is observed (Wu et al., 2018). And it makes the already unnatural neural
networks more elusive because we can’t expect our brain neurons to consider such a fine mathematical problem when making changes. Conditional-GAN(CGAN) based on the memory playback and the models based on the usage of knowledge distillation obtain good results. CGANs(Wu et al., 2018)(Seff et al., 2017) use the conditional batch normalization(Dumoulin et al., 2017) to extend its ability to generate label-conditioned images. Although solving the first conflict, the network structure stays the same and the second conflict remains. Methods using knowledge distillation(Zhai et al., 2019) need retrain a new randomly initialized model when new categories come. This retraining process make poor use of old knowledges. The most natural way is to extend the trained model dynamically.

We are inspired by the success of CVAE(Sohn et al., 2015) because of its simpleness and highly refined formulas. However, the CVAE formulas ignore the lasting effect of differences across categories when designing its objective function. It assumes that all categories images can be encoded to the latent representation following the same Gaussian distribution, but the significant differences between categories in the actual situation make this assumption unreasonable. We rewrite the CVAE formulas to supplement the above ignorance, and based on which we can make a novel interpretation about the role of CVAE’s condition input and find its selective activation function. Then we come to propose a dynamically growing CVAE structure to solve the second conflict. At the same time, applying memory playback and extending the one-way CVAE model to a circulatory mode allow our methods to solve the first conflict as well. In summary, our contributions are as follows:

- Rewrite the CVAE formulas, and provide a novel perspective for understanding the function of condition input and other parts of CVAE model.
- Utilize the CVAE to accomplish memory playback strategy, and extend it to a circulatory mode, providing a new method to solve the uncontinuous conflict.
- Equip the traditional CVAE model with dynamically growing structure, which provides a novel way to solve the ‘dead’ structure conflict.
- Conduct experiemnts on single-pattern MNIST dataset and on multi-patterns Fashion-MNIST dataset, which verify the effectiveness of our methods and the correctness of our understanding about CVAE.

2. Related Work

2.1. Conditional-VAE

Variational AutoEncoder(VAE)(Kingma & Welling, 2013) is an important kind of generative model proposed in 2013. In VAE, the visual data $x$ we can observe is assumed related to a latent vector $z$. The mapping function $x \rightarrow z$ is the recognition function $q_\phi(z|x)$, as well as the encoder in VAE. And $z \rightarrow x$ is the generative function $p_\theta(x|z)$, which is the decoder. VAE is designed to fit those two functions. It is now widely used to generate images, and when the generation model is trained, we can generate visual data $x$ with different shapes known as datas’ manifold(Rezende et al., 2014). Unlike generative adversarial networks(GANs)(Goodfellow et al., 2014)(Chen et al.), we know the density function(PDF) of the latent representation(or, we set it), while GANs dose not know such distribution.

VAE is a bayesian model, and the CVAE structure varies as different conditional probabilities are used(Kingma et al., 2014)(Walker et al., 2016)(Tang et al., 2017). Like developing GAN to conditional-GAN(Mirza & Osindero, 2014), the condition information is treated as part of the encoder’s inputs or decoder’s latent inputs in different CVAEs. So kinds of images can be generated according to given condition(Mishra et al., 2018)(Dorta et al., 2017). Pandey et al.(Pandey & Dukkipati, 2016) discussed how different categories will influence the encoding and decoding of the latent representation. They thought the condition information (i.e., different categories) is independent with the latent representation. In contrast, they also proposed conditional multimodal autoencoder(CMMA) trying to generate latent vector directly from condition information.

2.2. Continual Learning on Generative Tasks

About generative tasks, relatively less work studies the problem of continual learning and catastrophic fogetting. Seff et al. first introduced continual generative modeling and the idea of memory playback(Seff et al., 2017). Their approach incorporated elastic weight consolidation(EWC) into the loss function of GANs. Wu et al. explored the idea of memory playback futher and well accomplished the label-conditioned images generating tasks(Wu et al., 2018). They used conditional batch normalization on CGAN to extend their model’s ability to generate new categories images while remaining its structures. But their model presented limited capability in remembering previous categories.

Knowledge distillation is employed by Mengyao Zhai et al. to accomplish image-conditioned and label-conditioned generating tasks(Zhai et al., 2019). They use the cVAE-GAN model and make the networks learn new condition information by adding one more prior condition input (e.g., another size-fixed image in the image-conditioned model). They also used cLR-GAN model which applying condition information in the similar way. Both their model don’t need to change their structures. And when training on a new category, a new random initialized model is needed.
By forcing the old model and new model to generate the same auxiliary data, they can partly solve the catastrophic forgetting.

In this paper, we also apply the idea of memory playback. We introduce a new continual learning method which only contains a simple CVAE model. When a new category comes, our model can extend itself while remaining the trained parameters, and growing new ‘neurons’ (i.e., parameters) to learn new knowledges. We further illustrate its mathematical properties and find those categories-related parameters are updating independently, thus our model can distinct and remember different knowledges well. By applying our method, both two conflicts are rationally solved.

3. Approach

In this section, we will describe the proposed methods in details. We make discussions about the selective activation function of the One-Hot condition vector in CVAE based on the rewritten formulas. The understanding of the encoder and decoder will also be discussed. After the discussions, we naturally propose a dynamically growing structure. Finally, we discuss how to introduce the circulatory mode to better explore self-memory supervision.

3.1. CVAE Formulas and Work Principles

In original VAE proposed by Diederik P. Kingma and Max Welling, the visual data $x$ is transferred from a latent representation $z$. They build models to fit the transformation function by maximizing following variation bound:

$$-D_{KL}(q_{\theta}(z|x)||p_{\theta}(z)) + \mathbb{E}_{q_{\theta}(z|x)}[\log p_{\theta}(x|z)]$$  \hspace{1cm} (1)

And equation 2 is the corresponding original CVAE’s variation bound.

$$-D_{KL}(q_{\theta}(z|x,y)||p_{\theta}(z)) + \mathbb{E}_{q_{\theta}(z|x)}[\log p_{\theta}(x|z,y)]$$  \hspace{1cm} (2)

The KL divergence in equation 2 can be minimized under the assumption that $z \sim \mathcal{N}(0, 1)$. This assumption assumes that all categories can be encoded into a latent representation following the same distribution, while ignoring the lasting effect of categorical differences. We think that this ignorance causes fatal misunderstanding about CVAE structures. So we rewrite the condition variation bound as following:

$$-D_{KL}(q_{\theta}(z|x)||p_{\theta}(z|x)) - D_{KL}(q_{\theta}(y|x)||p_{\theta}(y|x)) + \mathbb{E}_{z}[\log p_{\theta}(x|z,y)]$$

In the rewritten formula, we separate the latent representation into two independent parts: ‘mixed’ part $q_{\phi_{1}}(z|x)$ and conditional part $q_{\phi_{2}}(y|x)$, then two KL divergences are observed. Applying the traditional CVAE’s assumption on $z$ to $q_{\phi_{1}}(z|x)$, we can minimize the first divergence. However, the second divergence is unoptimizable because we can’t know or make resonable assumptions about $q_{\phi_{2}}(y|x)$.

But we are shocked with the success of CVAE which has above ignorance, so we need to explain how it works.

![Figure 1. 1st MLP decoder layer with a Gassian noise and a One-Hot vector input.](image)

In Figure 1, we examine the the first decoder layer in CVAE which uses 2 layers Multi-Layer Perceptron (MLP) to build encoder and decoder, and One-Hot vector to represent condition information. We separate the first layer’s matrix into $W_c$ with $n_1$ columns and $W_p$ with $n_2$ columns, in which $n_1$ equals to the dimension of Gaussian noise $z$ and $n_2$ equals to the dimension of One-Hot vector $c$. As we can see, the result of $W_p \cdot c$ equals the $i$th column in $W_p$, which $c^i$ is 1. And the result of $W_c \cdot z$ is the sum of all $W_c$’s columns with different weights. In such decoding process, One-Hot vector exactly performs as a selective activator which activates different parameters in $W_p$. Then the output $(W_c \cdot z + W_p \cdot b)$ is passed to a activation layer and then to the second decoder layer, after which final visual data $\hat{x}$ will be generated.

Further more, as $W_c$ is categories independent while $W_p$ is categories dependent, we would like view $W_c$ as a common content generator and $W_p$ a private content generator. The reason that traditional CVAE performs well on generating label-conditioned images even can’t minimize the second divergence may that the One-Hot vector is a good replacement of $q_{\phi_{2}}(y|x^{(i)})$. We may refer to some widely-known neuroscience knowledges that one of the most fascinating functions of our brain is its complex activation and suppression process of different neurons. As the 0 element in $c$ prevents corresponding parameters from further forward propagation while 1 permits, One-Hot vector actually a wonderful replacement of $q_{\phi_{2}}(y|x^{(i)})$.

To briefly summarize, in CVAE structure, latent One-Hot vector input performs as a selective activator. Decoder performs as a generator that separately generates common content and private content. As $z$ is encoded from different
We further analyse the mathematical properties of such processes. Let $\partial J(W, b)$ denote the gradient of $J$ with respect to the weight $W$ and bias $b$. Their relationship with the objective function are shown in equation (4). The relationship between $\delta^l$ and $\delta^i$ are shown in equation (5).

$$\delta^l = \frac{\partial J(W, b)}{\partial z} = \frac{\partial J(W, b)}{\partial a} \cdot \sigma'(z)$$

$$\delta^i = \left( \frac{\partial z^{i+1}}{\partial z^i} \right)^T \delta^{i+1} = (W^{i+1})^T \delta^{i+1} \cdot \sigma'(z^i) \quad (5)$$

At each time, only one element isn’t zero in the One-Hot vector. So at each backpropagation process, the gradient of $W_p$ has the following property. Let $a_0$ be the One-Hot vector, $W_p^i$ be $W_p$’s $i^{th}$ column.

$$\frac{\partial J(W, b)}{\partial W_p^i} = \delta^i(a_0)^T \quad (6)$$

Further more,

$$\frac{\partial J(W, b)}{\partial W_p} = \begin{cases} \delta^i(a_0) & \text{if } i = 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Noting that after backpropagation, we have $W_p^i = W_p^i - \alpha \times \frac{\partial J(W, b)}{\partial W_p}$. Above property tells that because of the selective activation, in backpropagation, each categories-dependent parameters in $W_p$ update independently. However, the updation of $W_c$ is related with all categories. This important property conforms how we understand the term ‘private’ and ‘common’. And mathematically, it supports the correctness of our dynamically growing structure.

### 3.3. Losses and Circulatory mode

Our model contains three losses: traditional CVAE loss, circulatory loss, and self-memory supervision loss.

**Traditional CVAE Loss.** Applying our CVAE formula shown in equation (3), traditional one-way CVAE minimizes the first KL divergence between encoder recognized $q_{\phi_e}(z|x^{(i)})$ and the assumed latent distribution (i.e., Gaussian Distribution), and maximizes the likelihood probability of decoder generated visible data $\hat{x}$. Let $x$ denotes the available data in the newly comming category.

$$\zeta_{new} = \frac{1}{2} \sum_{i=1}^{t} (\mu_i^2 + \sigma_i^2 - \log \sigma_i^2 - 1) + BCELoss(x_{true}, \hat{x}) \quad (8)$$

Above loss doesn’t manage the second KL divergence in our formula. However, as we mentioned above, using the One-Hot vector as a replacement directly is a stable way to represent the latent distribution of condition information because of selective activation. ‘Stable’ means that it won’t make the output diverge even is ignored.

**Self-Memory Supervision and Circulatory Loss.** Figure 3 shows the self-memory supervision and circulatory process. When training newly growing neurons on new categories, we apply self-memory supervision. Before the training start, we call memory of unavailable categories using Gaussian noises and corresponding One-Hot condition.
Figure 3. Self-memory supervision and circulatory process.

Let $x_{\text{mem}}$ be generated unavailable data. $\hat{\mu}_i, \hat{\sigma}_i$ are latent representation recognized by encoder with input $\hat{x}_{\text{mem}}$.

$$
\zeta_{\text{mem}} = \frac{1}{2} \sum_{d} (\hat{\mu}_i^2 + \hat{\sigma}_i^2 - \log \hat{\sigma}_i^2 - 1) + \text{BCELoss}(x_{\text{mem}}, \hat{x}_{\text{mem}}) 
$$

In the traditional forward propagation, we generate visual data $\hat{x}$ and minimize the binary cross-entropy loss (BCELoss). This is a one-way mode because we don’t use of those generated images after the calculation of BCELoss. However, because the self-memory supervision process need those generated images as ‘real’ images later, so we need to make sure those images with enough features to accomplish the self-memory supervision. We extent the one-way mode to a circulatory one which means we will re-feed those generated images back to the model as warm-up operation. The circulatory loss is as follows:

$$
\zeta_{\text{mem}} = \frac{1}{2} \sum_{d} (\hat{\mu}_i^2 + \hat{\sigma}_i^2 - \log \hat{\sigma}_i^2 - 1) + \text{BCELoss}(\hat{x}, \hat{x}) 
$$

$\hat{\mu}_i, \hat{\sigma}_i$ are latent representations recognized by encoder with input $\hat{x}$. Because of this circulatory mode, we would like to refer our model as CYCLE-CVAE.

We don’t focus on how to improve self-memory supervision mathematically, so three losses have similar formulas. The total loss of our model is:

$$
\zeta_{\text{all}} = \zeta_{\text{new}} + \lambda_1 \zeta_{\text{eye}} + \lambda_2 \zeta_{\text{mem}} 
$$

$\lambda_1$ and $\lambda_2$ are set to balance three losses.

4. Experiments

In this section, we evaluate our methods on label-conditioned generation using MNIST\(^2\) and Fashion-MNIST\(^3\)(Xiao et al., 2017). And we compare our results\(^4\) with joint learning\(^4\) results using traditional CVAE. Additionally, in above discussions, the separation of common content and private content is a natural production of our methods. So we visualize what the common content looks like and how it changes along the training process. Another natural production is the steady feature of common content, more formally, the regression phenomenon of the common content. It means if the recognizer encodes common content well and the separation between common and private content has been successfully established, memories about old categories won’t be lost even not applying self-memory supervision when training on new categories. Both two productions and interesting results are presented below.

**MNIST and Fashion-MNIST:** Before moving on, we would like to state the reason for the choices of datasets. We call MNIST a single pattern dataset inspired by the using of *Seven-Segment Digital Tube*. Ten numbers can all be displayed by activating different segments. So the shape of the tube is what we think the single pattern as well as the common content hiding behind MNIST digits. And for Fashion-MNIST, we can’t point out that pattern directly. It contains T-shirt and Trousers (both clothes), Sandals and Ankle boot (both shoes). So we view Fashion-MNIST as a multi-patterns dataset. Single pattern means the existence of meaningful common content while multi-pattern may not. Using these two datasets as comparison will better evaluate our methods on different perspectives.

**Training Details:** We choose 2 layers MLP as CYCLE-CVAE’s encoder and decoder (Encoder: 784 → 256 → 2, Decoder: (2 + n2) → 256 → 784, n2 is the dimension of the One-Hot vector). To accomplish dynamically growing, after training on each category, we extend the first decoder layer from [256, 2 + n2] to [256, 2 + (n2 + 1)] by copy the trained parameters to corresponding positions and randomly initialize new parameters. We set epochs to 20 when training models on each category, learning rate to 0.001 and both $\lambda_1$ and $\lambda_2$ to 1.

**Quantitative Metrics:** To evaluate dynamically growing process, we focused on comparing this process to joint learning process which applying the same network structure. We use two metrics: Acc and r-Acc following Mengyao Zhai et al.\(^5\) (Zhao et al., 2019) to evaluate the generated images’ quantity. Acc is the accuracy using a classifier network trained on real images to evaluate generated images. r-Acc is the

\(^2\)url: http://yann.lecun.com/exdb/mnist/
\(^3\)More sample results are provided in supplementary material.
\(^4\)The model is trained on data from all categories.
accuracy using a classifier network trained on generated images to evaluate real images. The closer the two metrics on two processes are, the less side-effect dynamically growing process has.

### 4.1. Training Results and Comparision

First, we conduct experiments on MNIST digits. The visual results of JL and our methods are shown in Figure 4 (the rightmost is JL’s results).

![Figure 4. Training Results and Comparision on MNIST.](image)

|                | JL       | OURS     |
|----------------|----------|----------|
| MNIST Acc      | 99.2%    | 99.6%    |
| r-Acc          | 83.8%    | 83.2%    |

From the figure, we can see that our methods perform relatively well compared to JL. Meanwhile, VAE is famous about generate samples with different characters (known as data’s manifold), we can see our model somehow maintain this ability.

The quantitative metrics are shown in Table 1. Two metrics are quite close on two processes which demonstrate growing process doesn’t disrupt CVAE’s self-encoding ability.

Zhai et al. (Zhai et al., 2019) also conduct memory playback (MR) and knowledge distillation (KD) on MNIST. The Acc and r-Acc of MR are 97.54% and 85.57%, and of KD are 97.52% and 87.77%. Comparing with MR and KD, our methods can generate relatively high quality images from the Acc perspective. However, lacking of discriminator compared with GAN based models makes generated images with less details thus our methods’ r-Acc is a bit lower.

Second, we conduct experiments on the more challenging Fashion-MNIST dataset. The visual results of JL and our methods are shown in Figure 5 (the rightmost is JL’s results).

![Figure 5. Training Results and Comparision on Fashion-MNIST.](image)

|                | JL       | OURS     |
|----------------|----------|----------|
| FASHION-MNIST Acc | 82.1%    | 81.5%    |
| r-Acc          | 66.1%    | 64.2%    |

From the results, we can see our methods’ results are as quite ideal as we can expect. It distinguishes different categories well but more severe blurriness is observed. Quantitative metrics are shown in Table 2.

Comparing to the results on MNIST, two metrics differ larger on Fashion-MNIST as our expectation that multi-patterns dataset will disturb the effectiveness of learning common content. But they varies in an unsignificant range and dynamically growing process can manage abstract common content as well. This abstract common content we will see in following is actually a kind of regression phenomenon.

### 4.2. Visualization of Common Content

In this subsection, we will visualize what common content our models learn when it has been trained on all categories in MNIST. As Fashion-MNIST is a multi-patterns dataset, we are interested about how common content changes along training process, so we keep tracks on it after new categories have been trained.

We would like to first introduce the way to visualize common content. We separate the first decoder layer into \( W_c \) and \( W_p \). Parameters in \( W_p \) are selective activated by One-Hot vector which means each category will active different parameters. If we erase all selected parameters’ effects on \( W_c \cdot z \), then we may get the pure common content images. In experiments, we replace One-Hot vector by \( \vec{0} \in \mathbb{R}^{n2} \) to erase such effects.

![Figure 6. MNIST Common Content.](image)

In Figure 6, we visualize the common content learnt on MNIST. We may observe each sample with a cycle-like outline and one short bar at the cycle’s middle. It corre-
Lifelong Learning Strategy

responds to us Seven Segment Digital Tube inspiration.

Figure 7. Fashion-MNIST Common Content.

In Figure 7, each subfigure is one sample of common content\(^5\). When sample the leftmost common content, 5 categories are used and they are T-shirt, Trouser, Pullover, Dress and Coat. We can see the outputs perform high values in the images’ middle pixels while low values on each side. Generally, it looks like clothes if we combine each side pixels or looks like Trousers if we ignores those pixels. With the process going on, range of highlight pixels shrink to the middle. Note that Fashion-MNIST contains Sandal, Sneaker and Ankle boot. Those shoes images have high pixel values only in center positions. So the common content seems to highlight those pixels all categories have. Like a regression process, those pixels are the mean of different categories.

Figure 8. Common Content on Label 0, 2, 4 and 6.

To better convey the idea of common content, as comparison, we conduct experiments on Fashion-MNIST only using images with label 0, 2, 4 and 6 (i.e., T-shirt, Pullover, Coat and Shirt). Common content sample results are shown in Figure 8. Comparing to Figure 7, we can see that as we choose training images with more similar shapes, the common content become more meaningful and recognizable.

4.3. Steady Feature of Common Content

Finally, we would like to introduce the steady feature of the common content. From our experiments shown in Figure 6, we can conclude our interpretations about common contents and private content are reliable. So may we ask a question:

\(^5\)From left to right, number of already trained categories is 5, 6, 7, 8 and 10.

What if we don’t conduct self-memory supervision when training on a new category? For example, number 9 contains those common content and each one’s private contents are learnt independently. So maybe the answer is we won’t confront severe catastrophic forgetting. Figure 9 shows the sample result when we finished training on number 9 without calling memory about number 5. The Acc of such a model is around 99.5%, just as same as the result in Table 1. This means with other categories’ self-memory supervision, catastrophic forgetting isn’t observed on the generation of number 5.

Figure 9. Training on 9 Without Memory of Number 5.

Figure 10. Acc When lacking Self-Memory Supervision.

In Figure 10, we keep tracks on the Acc as we decrease self-memory supervision on more categories when training encoding label 9 (Number 9 in MNIST and Ankle boot in Fashion-MNIST). The x-axis denotes we don’t call memory
from label 0 to label $x$. Figure 11 and 12 keep tracks on the corresponding generation results. As shown in above figures, Acc performs significant decrease when the $x$ comes to 8 on both dataset, and before that it decreases gradually on Fashion-MNIST while remaining steadily high on MNIST. Along the process, generation results become less recognizable with a low pace. Noting that when $x$ comes to 8 means no self-memory supervision anymore, we can conclude that other categories are with enough knowledges to force the model keep the ability of encoding and decoding common content even the training data is severe label-absent. While the private content is learnt independently, it brings us above results. We call this the steady feature of common content as it performs high anti-interference when training new categories.

5. Conclusion

In this paper, we rewrote the CVAE’s formula and focused on the role of condition information. Such rewriting formula allowed us to make a new interpretation about the function of different parts in MLP based CVAE models. The selective activation function of the One-Hot condition vector we pointed out inspired us to propose a dynamically growing network. And combining this network with self-memory supervision process, using simple CVAE models, we were able to accomplish continuously learning on generation tasks. Besides, we extended traditional one-way CVAE to a circulatory mode to preheat the usage of memory datas. Unlike previous methods that reaining the network structure the same or retraining newly initialized network, our methods made the model dynamically extend itself and could well separate categories’ private content from common content. We validated our methods on the single-pattern MNIST and the multi-pattern Fashion-MNIST. Our experiments showed that dynamically growing process won’t significantly disturb traditional network’s ability. The visualization of common content and the regression phenomenon further verified the correctness of our interpretations mentioned above. The steady feature of common content was also presented.

References

Cao, Z. Realizing continual learning through modeling a learning system as a fiber bundle. CoRR, abs/1903.03511, 2019.

Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., and Abbeel, P. Infogan: Interpretable representation learning by information maximizing generative adversarial nets. In Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain, pp. 2172–2180.

Dorta, G., Vicente, S., Agapito, L., Campbell, N. D. F., Prince, S., and Simpson, I. Laplacian pyramid of conditional variational autoencoders. In Proceedings of the 14th European Conference on Visual Media Production (CVMP 2017), London, United Kingdom, December 11-13, 2017, pp. 7:1–7:9, 2017.

Dumoulin, V., Shlens, J., and Kudlur, M. A learned representation for artistic style. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings, 2017.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. C., and Bengio, Y. Generative adversarial networks. CoRR, abs/1406.2661, 2014.

Kingma, D. P. and Welling, M. Auto-encoding variational bayes. CoRR, abs/1312.6114, 2013.

Kingma, D. P., Mohamed, S., Jimenez Rezende, D., and Welling, M. Semi-supervised learning with deep generative models. In Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N. D., and Weinberger, K. Q. (eds.), Advances in Neural Information Processing Systems 27, pp. 3581–3589. Curran Associates, Inc., 2014.

Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A. A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., Hassabis, D., Clopath, C., Kumaran, D., and Hadsell, R. Overcoming catastrophic forgetting in neural networks. Proceedings of the National Academy of Sciences, 114(13):3521–3526, 2017.

McCloskey, M. and Cohen, N. J. Catastrophic interference in connectionist networks: The sequential learning problem. volume 24 of Psychology of Learning and Motivation, pp. 109 – 165. Academic Press, 1989.

Mirza, M. and Osindero, S. Conditional generative adversarial nets. CoRR, abs/1411.1784, 2014.

Mishra, A., Reddy, M. S. K., Mittal, A., and Murthy, H. A. A generative model for zero shot learning using conditional
variational autoencoders. In 2018 IEEE Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops 2018, Salt Lake City, UT, USA, June 18-22, 2018, pp. 2188–2196, 2018.

Nguyen, C. V., Li, Y., Bui, T. D., and Turner, R. E. Variational continual learning. CoRR, abs/1710.10628, 2017.

Pandey, G. and Dukkipati, A. Variational methods for conditional multimodal learning: Generating human faces from attributes. CoRR, abs/1603.01801, 2016.

Rezende, D. J., Mohamed, S., and Wierstra, D. Stochastic back-propagation and variational inference in deep latent gaussian models. CoRR, abs/1401.4082, 2014.

Seff, A., Beatson, A., Suo, D., and Liu, H. Continual learning in generative adversarial nets. CoRR, abs/1705.08395, 2017.

Sohn, K., Lee, H., and Yan, X. Learning structured output representation using deep conditional generative models. In Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M., and Garnett, R. (eds.), Advances in Neural Information Processing Systems 28, pp. 3483–3491. Curran Associates, Inc., 2015.

Tang, L., Xue, Y., Chen, D. L., and Gomes, C. P. Multi-entity dependence learning with rich context via conditional variational auto-encoder. In AAAI, 2017.

Titsias, M. K., Schwarz, J., de G. Matthews, A. G., Pascanu, R., and Teh, Y. W. Functional regularisation for continual learning using gaussian processes. CoRR, abs/1901.11356, 2019.

Walker, J., Doersch, C., Gupta, A., and Hebert, M. An uncertain future: Forecasting from static images using variational autoencoders. In Leibe, B., Matas, J., Sebe, N., and Welling, M. (eds.), Computer Vision – ECCV 2016, pp. 835–851, Cham, 2016. Springer International Publishing. ISBN 978-3-319-46478-7.

Wu, C., Herranz, L., Liu, X., Wang, Y., van de Weijer, J., and Raducanu, B. Memory replay gans: learning to generate images from new categories without forgetting. CoRR, abs/1809.02058, 2018.

Xiao, H., Rasul, K., and Vollgraf, R. Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms. CoRR, abs/1708.07747, 2017. URL http://arxiv.org/abs/1708.07747.

Zhai, M., Chen, L., Tung, F., He, J., Nawhal, M., and Mori, G. Lifelong gan: Continual learning for conditional image generation. In The IEEE International Conference on Computer Vision (ICCV), October 2019.