Memory Replay GANs: learning to generate images from new categories without forgetting

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Backgrounds

Continual Learning
: Rather than learning a single model with static, single-domain dataset, the model continually builds up its comprehensive ability on multiple tasks by learning on sequentially provided dataset.

- Computational systems operating in the real world are exposed to continuous streams of information and thus are required to learn and remember multiple tasks from dynamic data distributions.

- The ability to continually learn over time by accommodating new knowledge while retaining previously learned experiences is referred to as *continual* or *lifelong learning.*

- The main issue of continual learning is denoted as *catastrophic forgetting,* meaning that training a model with new information interferes with previously learned knowledge.

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Many papers tackling this issue are coming up in many conferences recently..
(more than 10 papers in ICRL2020)

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[Network Regularization]

EWC(Elastic Weight Consolidation)
:Regularizes the degree of changes of weights in the current task by defining the importance of weights in the last tasks.

- EWC++
- Online EWC

[Memory Replay]

Generative Replay
:Generates the datasets used in the last task and use them with the current dataset to train the model for the current task.

- Memory Replay GANs
- Dynamic Generative Memory

[Dynamic Architecture]

EWC(Elastic Weight Consolidation)
:Selectively expand the parameters of the model when the additional ones are necessary for the new tasks.

- Progressive Net
- LwF
- DAN
- Dynamic-expansion Net

Motivation

The generative task of learning new categories in a sequential fashion is tackled in this paper.

- This paper proposes that the generator has an active role by replaying memories of previous tasks.

- Replay generator is extended with two different methods introduced in this paper:
  1. Joint retraining with replayed samples
  2. Replay alignment

Replay generator has prevented the catastrophic forgetting mainly in deterministic task, but not in image generation.

- Image generation is a generative task and typically more complex than classification.

Proposed Methods

Non-sequential setting: Learning to generate the multiple classes at once

- The baseline is AC-GAN with WGAN-GP loss.
- Using category labels as conditions, the task is to learn from a training set $S = \{S_1, \ldots, S_M\}$ to generate images given an image category c.
- The framework consists of generator, discriminator and classifier.
  - Generator takes (z, c) to generate $\tilde{x} = G_{\theta^G}(z, c)$.
  - Discriminator discerns whether an input image is real or not.
  - Classifier predicts the label $\tilde{c} = C_{\theta^C}(x)$.
- Auxiliary classifier forces the generator makes images to be classified in the same way as real images.

$$\min_{\theta^G}(L^G_{GAN}(\theta, S) + L^G_{CLS}(\theta, S))$$

$$L^G_{GAN}(\theta, S) = -E_{z\sim p_z, c\sim p_c}\left[D_{\theta^D}\left(G_{\theta^G}(z, c)\right)\right]$$

$$L^G_{CLS}(\theta, S) = -E_{z\sim p_z, c\sim p_c}[y_c log C_{\theta^C}\left(G_{\theta^G}(z, c)\right)]$$

$$\min_{\theta^D, \theta^C}(L^D_{GAN}(\theta, S) + L^D_{CLS}(\theta, S))$$

$$L^D_{GAN}(\theta, S) = -E_{(x,c)\sim S}\left[D_{\theta^D}(x)\right] + E_{z\sim p_z, c\sim p_c}\left[D_{\theta^D}\left(G_{\theta^G}(z, c)\right)\right]$$

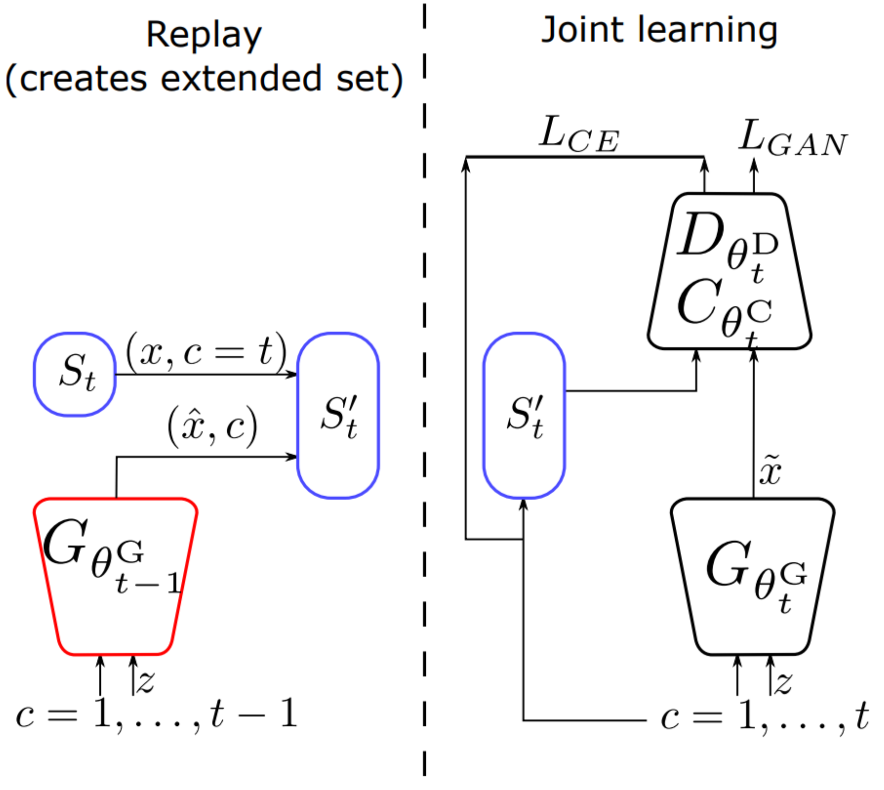
$$+ \lambda_{GP} E_{x\sim S, z\sim p_z, c\sim p_c, \epsilon\sim p_\epsilon}[\left(\left\|\nabla D_{\theta^D}\left(\epsilon x + (1-\epsilon) G_{\theta^G}(z, c)\right)\right\|_2 - 1\right)^2$$

$$L^D_{CLS}(\theta, S) = -E_{(x,c)\sim S}[C_{\theta^C}\left(G_{\theta^G}(z, c)\right)]$$

Proposed Methods

Sequential setting: Learning to generate the class one by one in a sequential manner

1. Joint retraining with replayed samples



(a) Joint retraining with replay

- Compared to DGN, a conditional GAN where (x, c) pair is input allows us finer control of the replay process, avoiding potential classification errors and biased sampling towards the recent categories.

- This method creates an extended dataset $S'_t = S_c \cup \tilde{S}_{c\in\{1,\ldots,t-1\}}$, where S_c denotes the real training data for current task, $\tilde{S}_c$ denotes the memory replays from previous tasks.

$$\min_{\theta_t^G}\left(L_{GAN}^G(\theta_t, S'_t) + \lambda_{CLS} L_{CLS}^G(\theta_t, S'_t)\right)$$
$$\min_{\theta_t^D}\left(L_{GAN}^D(\theta_t, S'_t) + \lambda_{CLS} L_{CLS}^D(\theta_t, S'_t)\right)$$

Proposed Methods

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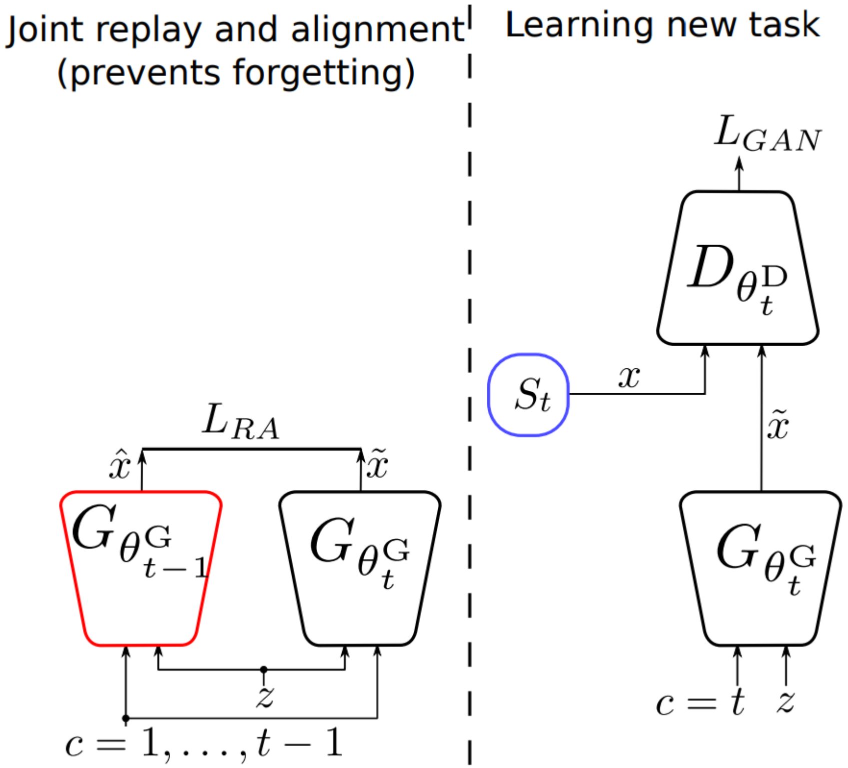
2. Replay Alignment



(b) Replay alignment

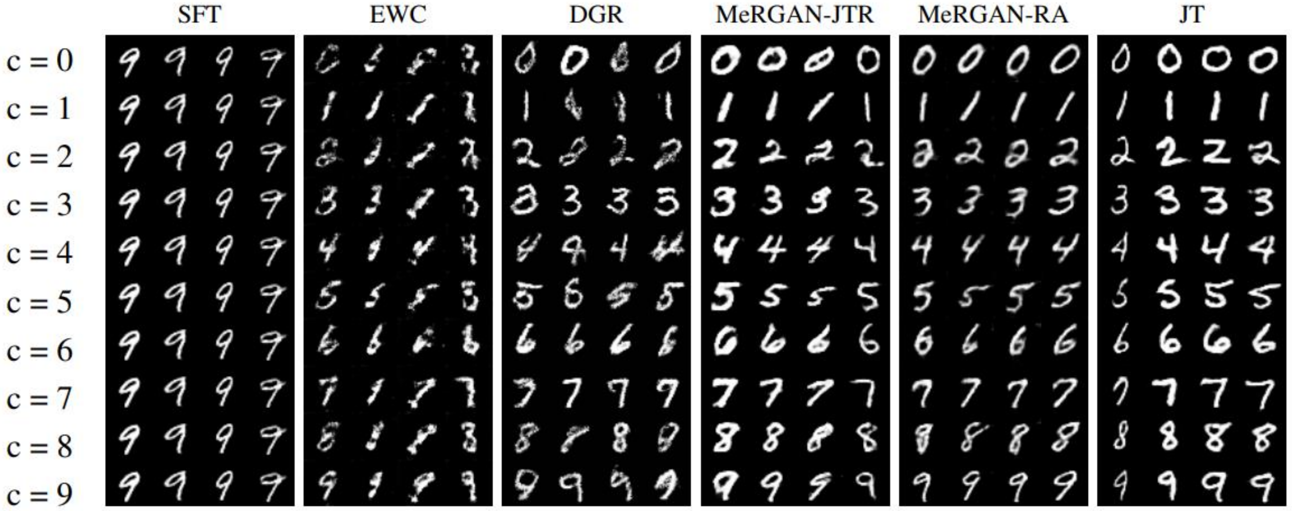
- The current generator is first initialized with the same parameters of the replay generator, both of them can be synchronized to generate the same image by the same category c and latent vector z as inputs.

- In these conditions, the generated images $\hat{x}$ from the replay generator and $\tilde{x}$ from the current generator should be aligned pixelwise.

$$\min_{\theta_t^G}\left(L_{GAN}^G(\theta_t, S_t)\right) + \lambda_{RA} L_{RA}(\theta_t, S_t)$$

$$L_{RA}(\theta_t, S_t) = E_{x \sim S, z \sim p_z, c \sim U\{1, t-1\}}\left[\left\| G_{\theta_t^G}(z, c) - G_{\theta_{t-1}^G}(z, c)\right\|^2\right]$$

Experiments



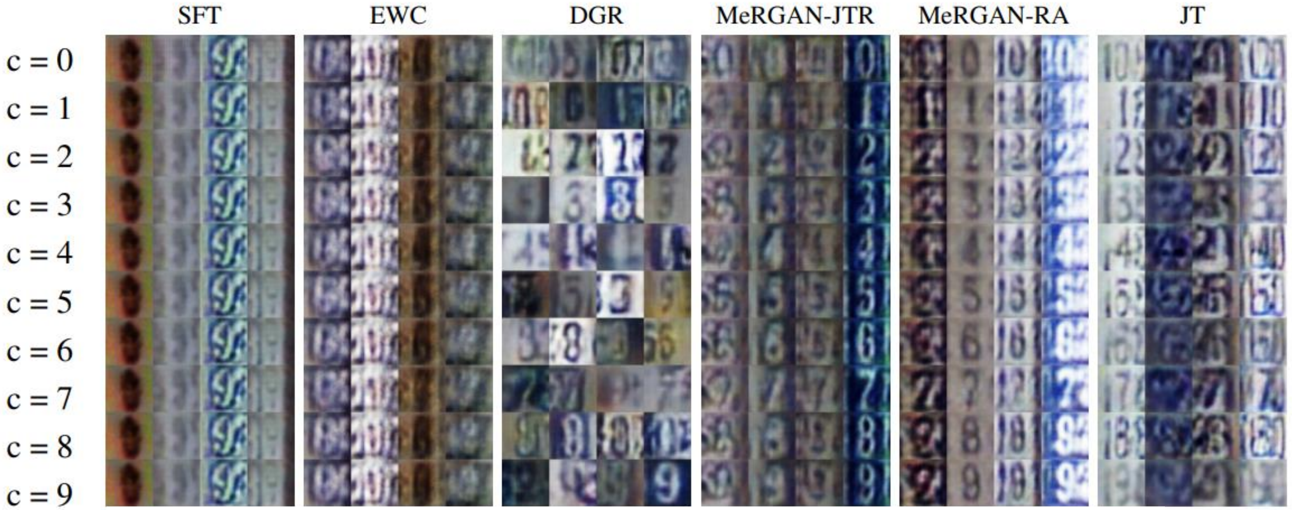
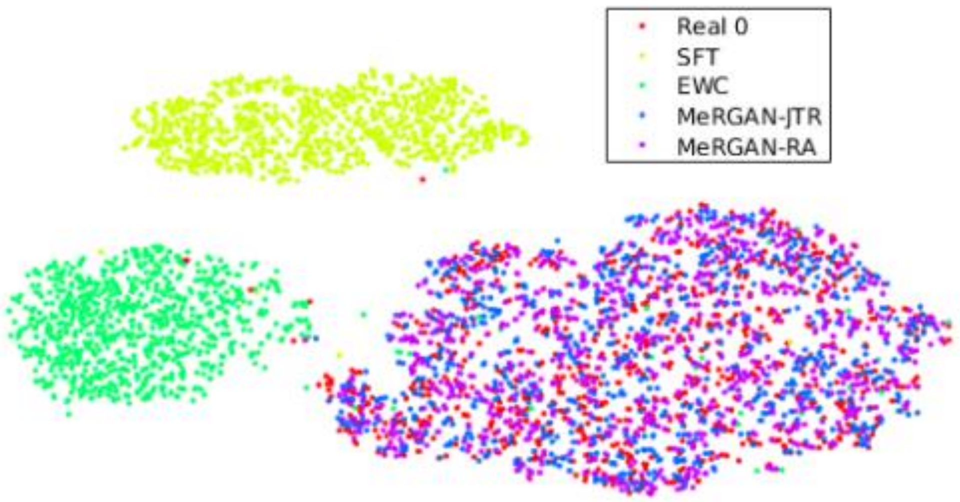


Table 1: Average classification accuracy (%) in digit generation (ten sequential tasks).

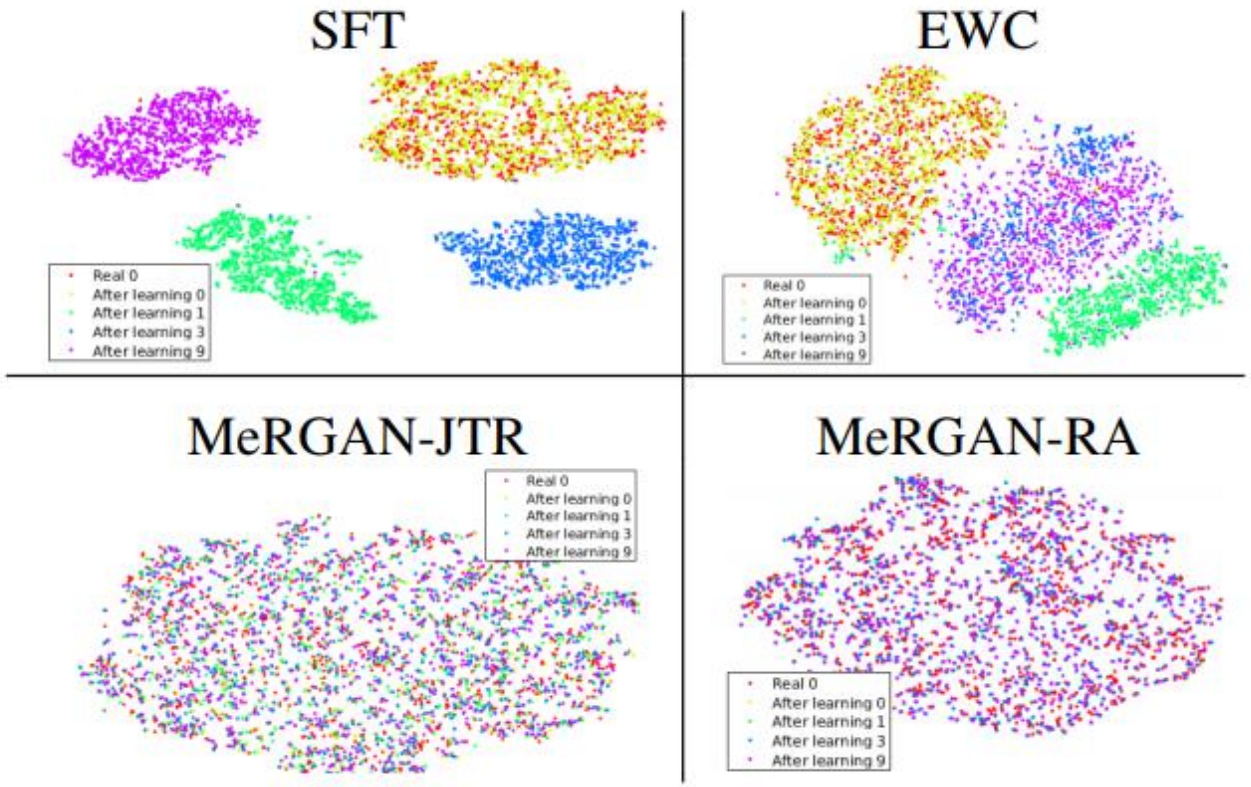
	5 tasks (0-4)						10 tasks (0-9)					
	Baselines		Others		MeRGAN		Baselines		Others		MeRGAN	
	JT	SFT	EWC[26]	DGR[27]	JTR	RA	JT	SFT	EWC[26]	DGR[27]	JTR	RA
MNIST	97.66	19.87	70.62	90.39	**97.93**	**98.19**	96.92	10.06	77.03	85.40	**97.00**	**97.01**
SVHN	85.30	19.35	39.84	61.29	**80.90**	**76.05**	84.82	10.10	33.02	47.28	**66.50**	**66.78**

- Sequential fine-tuning(SFT) and non-sequential joint training(JT) are lower-bound and upper-bound, respectively.
- Generation for SVHN is more challenging with relatively limited capacity of model.
- Qualitatively reliable and better results are generated from MeRGAN methods compared to others.
- Higher classification accuracy is achieved in MeRGAN methods.

Experiments



(a) After all tasks



(b) After tasks 0,1,3,9

- A classifier trained with real digits is used to extract the embeddings of the methods.
- The distributions of 0s generated by MeRGANs greatly overlap with the distributions of real 0s.
- No isolated clusters of real samples are observed, which suggests that MeRGANs prevent forgetting better while keeping diversity.

Experiments

Experiments

Table 2: FID and average classification accuracy (%) on LSUN after the 4th task

	SFT	EWC	DGR	MeRGAN-JTR	MeRGAN-RA
Acc.(%)	15.02	14.28	15.40	79.19	**81.03**
Rev acc.(%)	28.0	63.35	26.17	70.00	**83.62**
FID	110.12	178.05	93.70	49.69	**37.73**

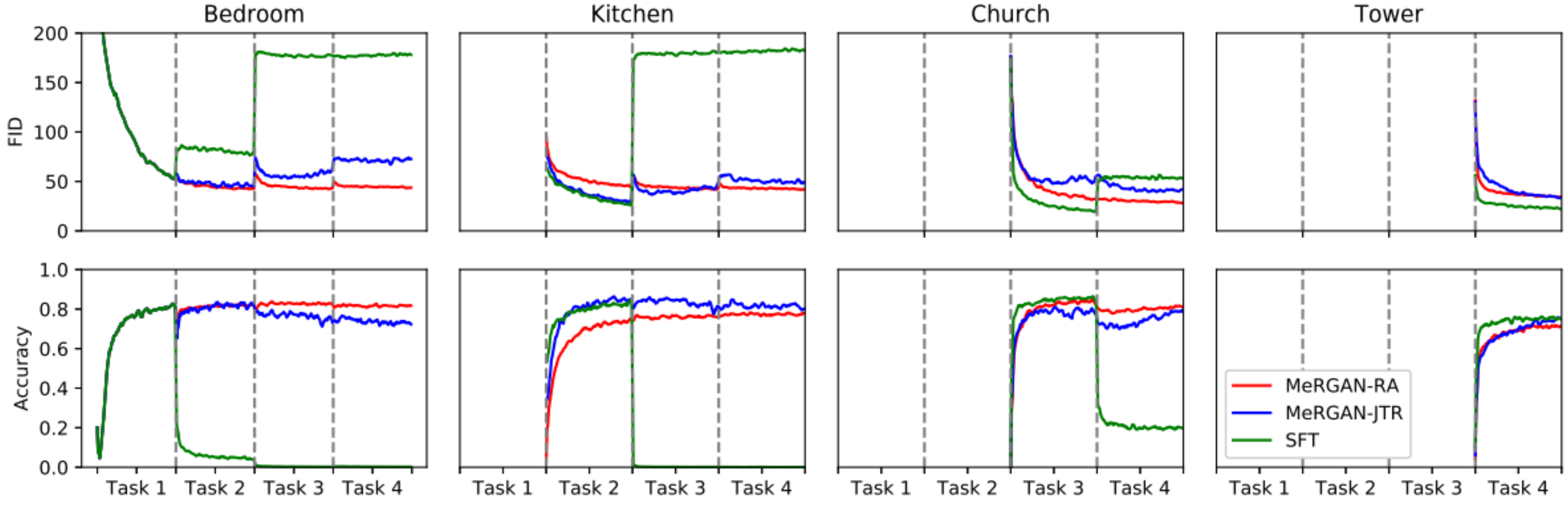


Figure 6: Evolution of FID and classification accuracy (%). Best viewed in color.

- Reverse accuracy measured by a classifier trained with generated data and evaluated with real data.
- Frechet inception score(FID) measures both quality and diversity.