Generative Memory for Continual Learning

Ivan Skorokhodov

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Contents

Deep Generative Replay (DGR) [1]

Main idea (1/3)

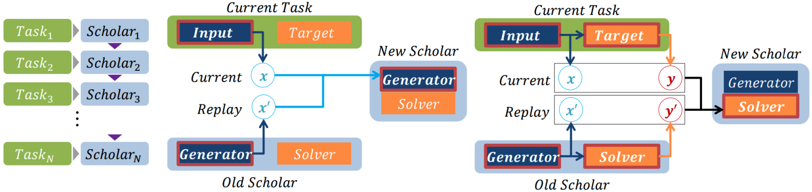
- Train a generator G_1, train a classifier C_1 for task #1
- For task $t > 1$ generate images with G_{t-1}, generate labels with C_{t-1} to obtain a dataset $\hat{D}_{:t}$
- Train on both $\hat{D}_{:t}$ and D_t (real data for task t) jointly
- Note: it's not clear from the paper if they trained C_t on the logits of C_{t-1} or its one-hot predictions
- Note: it's a bit odd that they do not train conditional generator

$$\mathcal{L} = r \underset{(\boldsymbol{x},\boldsymbol{y})\sim D_i}{\mathbb{E}} \left[L\left(C_t(\boldsymbol{x}), \boldsymbol{y}\right)\right] + (1-r) \underset{\boldsymbol{x}'\sim G_{t-1}}{\mathbb{E}} \left[L(C_t(\boldsymbol{x}'), C_{t-1}(\boldsymbol{x}'))\right]$$

[1] "Continual Learning with Deep Generative Replay" by Shin et al., NeurIPS 2017

Deep Generative Replay (DGR)

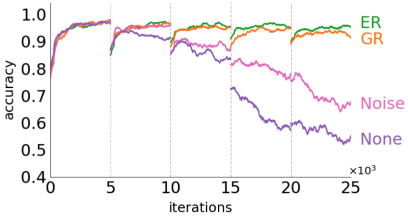
Illustration (2/3)



(a) Sequential Training (b) Training Generator (c) Training Solver

Deep Generative Replay (DGR)

Results on permuted MNIST (3/3)



- 5 tasks
- ER — Joint Multi-Task baseline
- Noise — feeding random noise instead of images into C_{t-1} to distill knowledge

Memory Replay GAN [2]

Main idea (1/3)

- Idea is simple: train a generative memory G_t, save its snapshot before each new task and distill its knowledge into a new one G_{t+1}
- There are two ways to distill the knowledge
  - Generate synthetic data and mix it into a new one S'_t (Joint Retraining)
  - Perform real knowledge distillation (Replay Alignment):

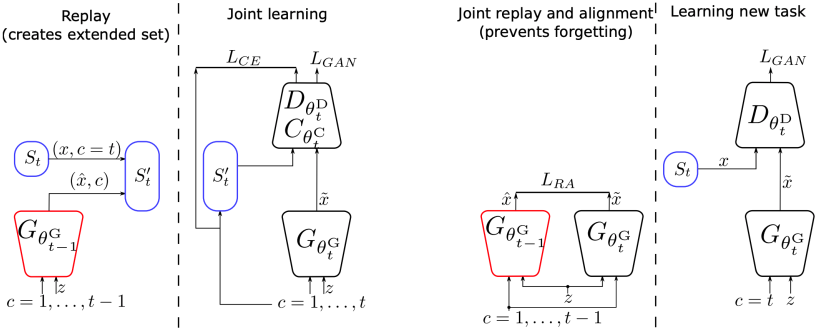
$$\mathcal{L}_G = L_G(\theta_t, S_t) + \lambda \underset{z \sim p_z, c \sim U(0, t-1)}{\mathbb{E}} \left[\left\| G_t(z, c) - G_{t-1}(z, c) \right\|^2 \right]$$

- Also train a classifier on top of GAN

[2] "Memory Replay GANs: Learning to Generate New Categories without Forgetting" by Wu et al., NeurIPS 2018

Memory Replay GAN (MeRGAN)

Illustration (2/3)

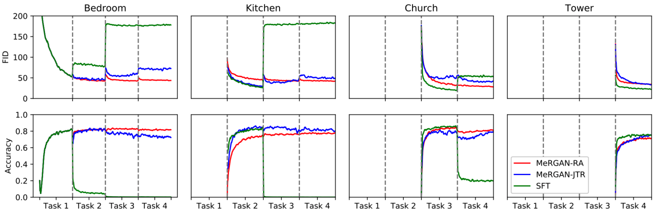


(a) Joint retraining with replay

(b) Replay alignment

Memory Replay GAN (MeRGAN)

Results (3/3)



- SFT (sequential fine tuning) is no tricks at all
- Replay Alignment tends to work better
- Authors are not clear about how they have measured the accuracy, as far as I got — they have trained a classifier on real data and measured its performance on the fake data.

Dynamic Generative Memory (DGM) [4]

Main idea (1/3)

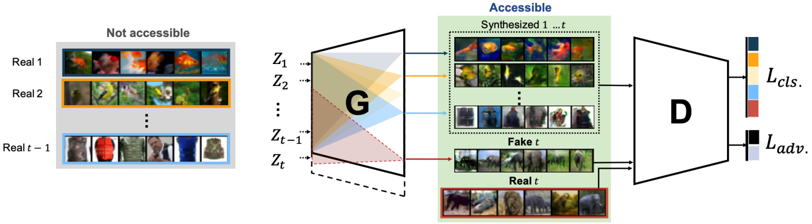
- Authors consider class-incremental learning (just as we do): classes arrive sequentially and we evaluate the performance on all the tasks
- They do not run any kind of knowledge distillation and follow HAT[3] approach instead
- More precisely, for task t, for layer l of the generator they train a binary mask m_l^t and multiply layer's weights on this mask
- Binary mask m_l^t is regularized to be sparse
- Previously learned weights are not updated in the future (but network can learn to ignore them by learning the corresponding mask)
- But compared to HAT, authors are cheating: they add new neurons to the generator after each task to preserve its capacity

[3] "Overcoming Catastrophic Forgetting with Hard Attention to the Task" by Serra et al., ICML 2018

[4] "Learning to Remember: A Synaptic Plasticity Driven Framework for Continual Learning" by Ostapenko et al., arxiv

Dynamic Generative Memory (DGM)

Illustration (2/3)



Dynamic Generative Memory (DGM)

Results (3/3)

	Method	MNIST (%) A_5	MNIST (%) A_{10}	SVHN(%) A_5	SVHN(%) A_{10}	CIFAR10(%) A_5	CIFAR10(%) A_{10}	ImageNet-50(%) A_{30}	ImageNet-50(%) A_{50}
	JT	99.87	99.24	92.99	88.72	83.40	77.82	57.35	49.88
Episodic memory	iCarl-S [22]	-	55.8	-	-	-	-	29.38	**28.98**
	EWC-S[9]	-	79.7	-	-	-	-	-	-
	RWalk-S[2]	-	82.5	-	-	-	-	-	-
	PI-S [34]	-	78.7	-	-	-	-	-	-
Generat. memory	EWC-M [28]	70.62	77.03	39.84	33.02	-	-	-	-
	DGR [30]	90.39	85.40	61.29	47.28	-	-	-	-
	MeRGAN [31]	98.19	97.00	80.90	66.78	-	-	-	-
	DGMw (ours)	98.75	96.46	**83.93**	**74.38**	**72.45**	**56.21**	**32.14**	17.82
	DGMa (ours)	**99.17**	**97.92**	81.07	66.89	71.91	51.75	25.93	15.16

- Here A_n is the performance on n previously seen classes
- For ImageNet-50 they train for 5 tasks, 10 classes per task
- They do not state it clearly, but as far as I got they use 5 and 10 tasks for other datasets

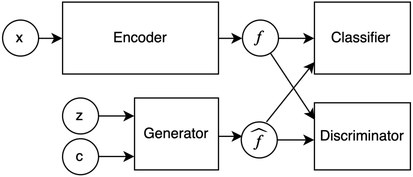
Latent Generative Memory

Main idea (1/2)

- Let's get rid of separate knowledge distillation step (it is questionable both biologically and practically)
- So let's train GM and Classifier jointly
- Since training GM in the visual space is tough, let's train it in the feature space
- Make the GM reside in "deep" layers of the Classifier and hallucinate

Latent Generative Memory

Illustration (2/2)



- For task $t = 1$ we train the model normally
- For task $t > 1$ generate a lot of fake memories with G_{t-1} of previously seen classes
- Train Classifier to correctly distinguish these fake memories
- Question #1: how to avoid knowledge distillation for Generator?
- Question #2: what if Encoder will start changing the embedding manifold? Then our fake memories will not correspond to actual embeddings. Maybe we can introduce prototypes to resolve this?

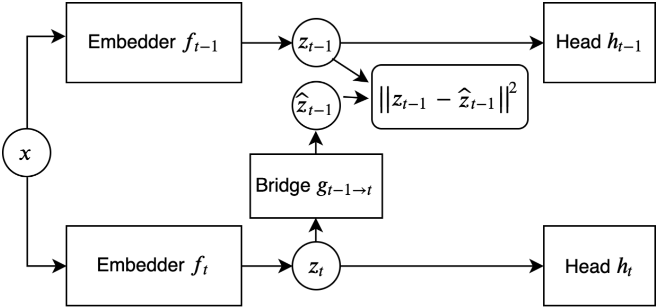
Latent Space Alignment

Main idea (1/2)

- It's not about generative memory (but can be useful)
- Imagine our classifier is $h(f(x))$, where $f(x)$ is an embedder and $h(z)$ is a head
- We work in multi-headed setup, i.e. we have a separate head $h_t(z)$ for each task t
- In this setup forgetting occurs when embedder $f(x)$ changes
- Imagine that head $h_{t-1}(z)$ was operating in embedding space Z_{t-1}, but task t changed it and $h_t(z)$ operates in Z_t
- Let's train a "bridge" function $g_{t \to t-1} : Z_t \to Z_{t-1}$ which will convert Z_t to Z_{t-1}
- Having good bridges between all the latent spaces $Z_T \to Z_{T-1} \to ... \to Z_2 \to Z_1$ we'll be able to compute predictions with embedding $f_T(x)$ without forgetting
- An interesting consequence is that we can train 10 models on 10 tasks in parallel and then just align their latent spaces

Latent Space Alignment

Illustration (2/2)



- After we have trained a bridge $g_{t \to t-1}$ we can discard f_{t-1} since we can always compute original predictions by $h_{t-1}(g_{t \to t-1}(f_t(x)))$

Online Generative Memory

Main idea:

- Idea is to keep model not to change its previous predictions
- Maybe we can adapt it to LwF scenario (but LwF does not work well even as it is)

Three ideas on how to achieve this

- MAML-like way:
  1. Perform k steps in $\nabla \| f_\theta(x_k) - f_{\theta - \nabla L(\theta)}(x_k) \|_2^2$ direction
  2. Safely perform step in $\nabla L(\theta)$ direction.
- Teacher distillation with previous batch after the current update
  1. Generate and save a batch of examples
  2. Perform gradient step for the main loss
  3. Perform teacher distillation step with the saved batch
  4. Repeat
- Project GD step onto $\|f(x) - y\| \leq \varepsilon$ space (wrt spectral or frobenius norm)
  1. Generate and save a batch of examples X
  2. Compute a gradient for the main loss
  3. Project the gradient onto $f(x) = y$ loss by projecting the gradient for each layer