MIDTERM 4

Continual Learning with Deep Generative Replay

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The setting

- Deep learning is the state-of-the-art tool to solve many complex tasks.
- The trend has been to go towards **more and more complicated problems**, but in **narrow domains.**
- The scenario was usually **offline learning**, where the training data is all available prior to the deployment of the model.

This creates problems in terms of **adaptability** and **versatility** of the model, as well as of **scalability** and **feasibility** in some real-world applications.

Continual Learning

- **Continual learning** is a framework where the model learns sequentially from a stream of experiences.
- Data can become available during time
- No access to previously encountered data is necessary (depends on the approach)
- Constant computational and memory resources (depends on the approach)

The problem

"Attempts to train a comprehensive artificial intelligence capable of solving multiple tasks have been impeded by a ***chronic problem*** *called* ***catastrophic forgetting****"* [1]

Catastrophic Forgetting

- Problem where the model's **performance on previously learnt tasks degrades** when the model is trained on a new task because the parameters are optimized for the new one without considering the previous knowledge.
- **Stability** vs **plasticity** tradeoff
- It is **not sustainable** to train the model **from scratch** for every new experience

Some solution approaches

Regularization-based

- Elastic weight consolidation (Kirkpatrick et al, 2017)
- Learning without forgetting (Li et al, 2018)

Rehersal-based

- Rehearsal and Pseudorehersal (Robins, 1994)

More advanced replay strategies

- ***Generative Replay*** (Shin et al, 2017)
- Distilled Replay (Rosasco, Carta, Cossu, Lomonaco, Bacciu, 2021)

[1] Hanul Shin, Jung Lee, Jaehong Kim, Jiwon Kim. *Continual Learning with Deep Generative Replay*, 2017

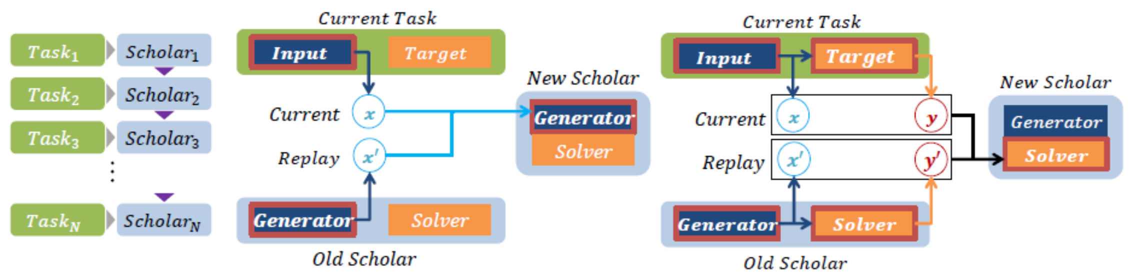
Deep Generative Replay

Scholar model
- capable of **learning** a new task and **teaching** its knowledge to other networks.
- Composed by a **generator** and a **solver**

Solver: Task-solving model (neural network)

Generator
- Deep generative model → **GAN**
- **Adversarial training** of generator and discriminator
- **Generator** learns to **mimic** real data distribution
- **Discriminator** learns to **distinguish** between real and generated data

Training
- **Sequential** training on **scholar** model
- Train current scholar while referring to recent copy of the network → current scholar learns from past one
- Equivalent to train a sequence of scholars



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

1) Generator training
- New generator (G) receives current task's input (**x**) and *replayed* inputs from previous tasks (**x'**)
- **x'** generated by the previous scholar's generator
- G learns to reconstruct **cumulative** input space

2) Solver training
- New solver (S) learns to couple inputs and targets from mix of real and replayed data
- Replayed targets are past solver's response to replayed inputs

More in depth

$$\underbrace{L_{train}(\theta_i) = r}_{}\mathbb{E}_{(\boldsymbol{x},\boldsymbol{y})\sim D_i}\underbrace{[L(S(\boldsymbol{x};\theta_i),\boldsymbol{y})]}_{} + (1-r)\,\mathbb{E}_{\boldsymbol{x}'\sim G_{i-1}}\underbrace{[L(S(\boldsymbol{x}';\theta_i),S(\boldsymbol{x}';\theta_{i-1}))]}_{}$$

Previous generator

r is the **ratio** between the importance of the **new task** compared to the **older ones**

Loss of the solver with **real data** and **real targets**

Loss of the solver where the **data** is **generated** by the previous generator and the **targets** are the **previous solver's response** to those same inputs

$$L_{test}(\theta_i) = r\mathbb{E}_{(\boldsymbol{x},\boldsymbol{y})\sim D_i}[L(S(\boldsymbol{x};\theta_i),\boldsymbol{y})] + (1-r)\,\mathbb{E}_{(\boldsymbol{x},\boldsymbol{y})\sim D_{past}}[L(S(\boldsymbol{x};\theta_i),\boldsymbol{y})]$$

Cumulative distribution of past data

At test time, no self-generated inputs are used

Preliminary experiment

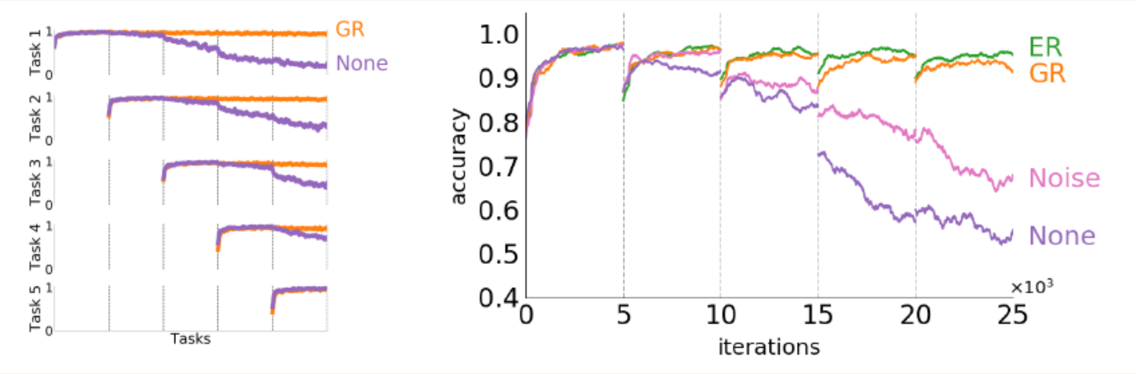
- A trained scholar model alone suffices to train an "empty" network.
- It's shown that scholar models transfer knowledge without loosing information.

Table 1: Test accuracy of sequentially learned solver measured on full test data from MNIST database. The first solver learned from real data, and subsequent solvers learned from previous scholar networks.

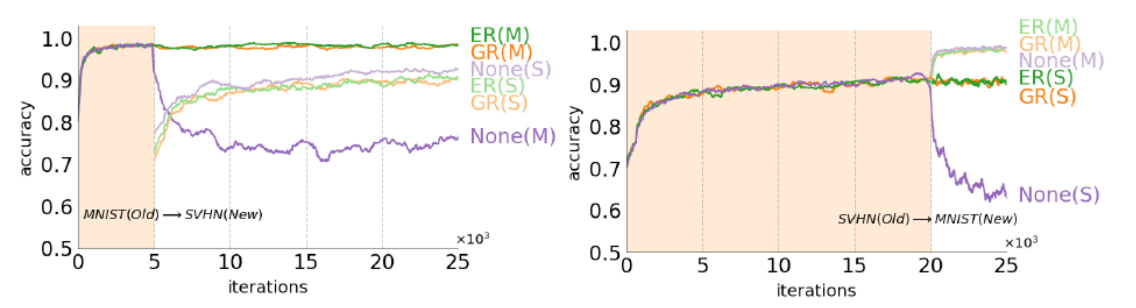
	$Solver_1$	$\rightarrow$	$Solver_2$	$\rightarrow$	$Solver_3$	$\rightarrow$	$Solver_4$	$\rightarrow$	$Solver_5$
Accuracy(%)	98.81%		98.64%		98.58%		98.53%		98.56%

Experiments

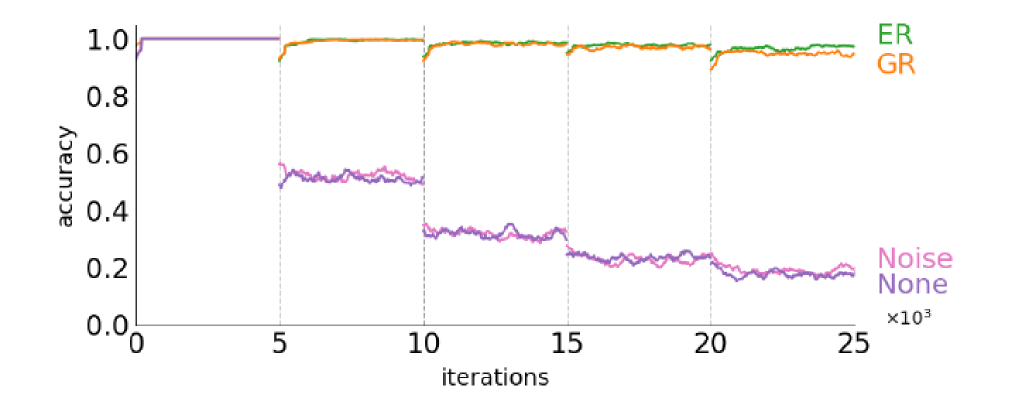
Independent tasks
- Image classification on MNIST
- Pixels shuffled by permutation unique to each task
- Solver must classify permuted inputs to original class



Learning new domains
- Model sequentially trained to classify MNIST and SVHN numbers



Learning new classes
- Model sequentially trained on mutually exclusive subsets of classes
- Solver must eventually classify examples from all classes



Conclusion

- GR has the advantage of **not needing any memory**
  - Unlike rehearsal strategies
  - Maintain former knowledge solely from input-target pairs produced by the saved network
  - Ease of balancing performances on former and new tasks, but old tasks are balanced as a whole

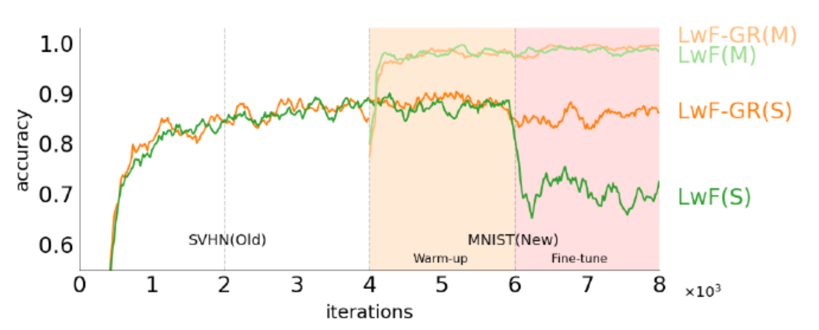
- GR has a **constant computational time**
  - No extra parameters for each task like in LwF, where training time linearly increases for each new task

- GR is **not** regularization-based
  - Approaches such as EWC might suffer from the tradeoff between performances on old tasks and new tasks

- The **quality of GR** heavily **depends** on the quality of the **generator**
  - But improvements in training generative models can be directly reflected into improvements in GR

- Generated samples can represent well the data distribution
  - But they might be less dense of information compared to *Distilled Replay*, thus more samples would be necessary to mitigate forgetting

- LwF needs context about the task that's being performed (to use a task-specific output layer), GR does not.
  - GR can be used to augment LwF, adding samples similar to former tasks inputs (instead of using only current task's inputs to revoke past knowledge)



THANK YOU FOR YOUR ATTENTION

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