Pseudo Rehearsal using non photo-realistic images

Bhasker Sri Harsha Suri
Computer Science Department
Indian Institute of Technology Tirupati
Tirupati, Andhra Pradesh
Email: cs18s506@iittp.ac.in

Kalidas Yeturu
Computer Science Department
Indian Institute of Technology Tirupati
Tirupati, Andhra Pradesh
Email: ykalidas@iittp.ac.in

***Abstract*—Deep neural networks forget previously learnt tasks when they are faced with learning new tasks. This is called *catastrophic forgetting*. *Rehearsing* the neural network with the training data of the previous task can protect the network from catastrophic forgetting. Since rehearsing requires the storage of entire previous data, *Pseudo rehearsal* was proposed, where samples belonging to the previous data are generated synthetically for rehearsal. In an image classification setting, while current techniques try to generate synthetic data that is photo-realistic, we demonstrated that Neural networks can be rehearsed on data that is not photo-realistic and still achieve good retention of the previous task. We also demonstrated that forgoing the constraint of having *photo realism* in the generated data can result in a significant reduction in the consumption of computational and memory resources for pseudo rehearsal.**

I. Motivation

Artificial neural networks have successfully demonstrated their ability to learn and perform on tasks that demand complex cognitive capabilities. However, current Neural Network architectures are incapable of learning new tasks sequentially. Whenever a neural network attempts to learn a new task, it forgets the task that it learnt previously. This problem is called *catastrophic forgetting* Generative replay is a technique where the training data for the previous task is synthetically generated using a generator. Generative Adversarial Networks(GAN) are a popular choice for creating this synthetic data. However, GANs cannot generate synthetic data for visually complex images. To solve this problem, we propose usage of Genetic Algorithms to generate the synthetic data. Instead of generating photo-realistic images, we propose generating images which when trained upon have the boundary preserving properties required to prevent forgetting.

II. Conclusion

In this work, we demonstrated that in an image classification setting, pseudo rehearsal can be performed by ignoring the *photo-realism* of the generated samples. We also showed that by ignoring the constraint of photo-realism of the generated synthetic samples, we can achieve high retention capacities of the previous task while consuming modest computational and memory resources. We also demonstrated that the proposed technique is scalable to *visually complex* datasets unlike existing techniques in the literature.

III. Algorithm

Algorithm 1 Synthetic data generation for a class c

P: $\{x_0, x_1, x_2 ... x_{m-1}\}$ // Random population
$|P| = m$
while $(\exists x \in P) : f_c(x) \leq \tau$ **do**
  $P' = \{< x, f_c(x) > |\forall x \in P\}$
  Let, L be a list in descending order of $f_c(x), \forall x \in P'$
  $P^* = L[0 \ldots m * 0.25]$ //top 25% of elements
  $C = [crossover(P^*[j], P^*[j+1])|\forall j \in [0 \ldots |P^*| - 1]]$
  $M = [mutation(x)|\forall x \in P^*]$
  $M_C = [crossover(M[i], M[i+1])|\forall i \in [0, \ldots, |M| - 1]]$
  $P_{new} = P^* \cup C \cup M \cup M_C$
  $P = P_{new}$
end while

Here $f_c(x) = \frac{e^{z_c}}{\sum_{j=1}^{K} e^{z_j}}$
where z is vector of scores for each of the classes $1 \ldots K$, c is the given target class, $f_c(x)$ is softmax score for class c on input x and K is the total number of classes.

IV. Enrichment phase

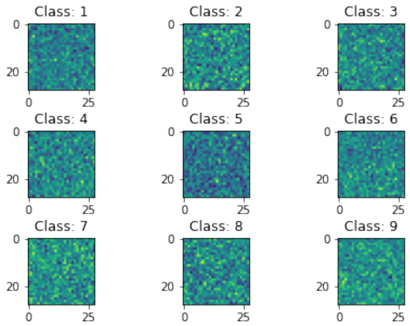
The Genetic Algorithm is followed by an *Enrichment phase* where the number of synthetic samples are increased using Gaussian mixture models. It is a two step process. In the first step, one Gaussian is fitted to each class and in the second step one Gaussian is fitted to the entire synthetic data.

V. Agreement score

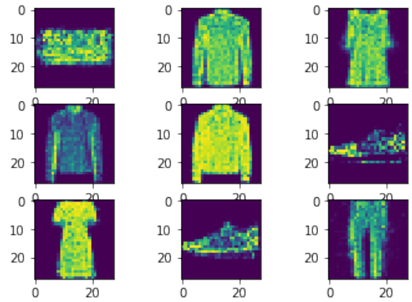
A new metric was also proposed to compare the behaviour of models trained on synthetic data and original data. Here, the predictions of the models are compared on a control dataset irrespective of their correctness.

$$\alpha(P_M, P_N) = \frac{\theta}{|T|} * 100 \quad (1)$$

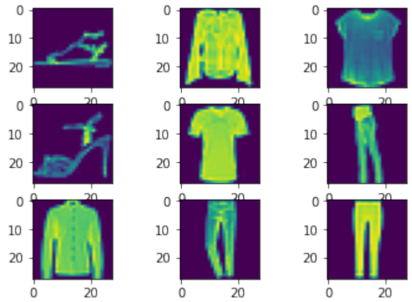
where P_M and P_N are the predictions of model M and model N on some test dataset. θ is the number of identical predictions, $|T|$ is the size of the test data.



(a) Our technique

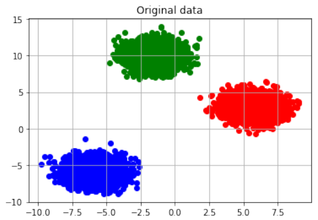


(b) GAN generated images

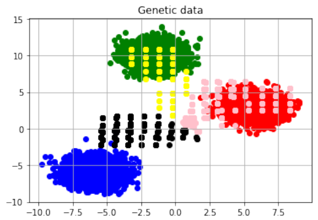


(c) Original images

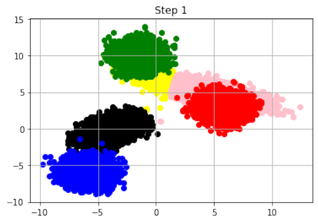
Fig. 1: A comparison of Genetically generated images and GAN generated images with Original images.



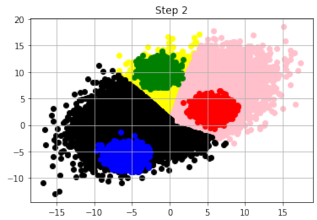
(a)



(b)

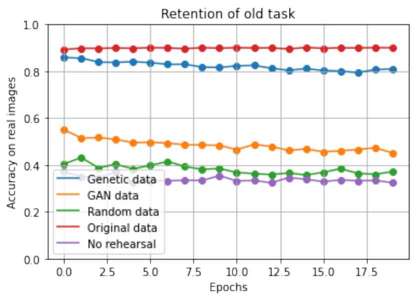


(c)

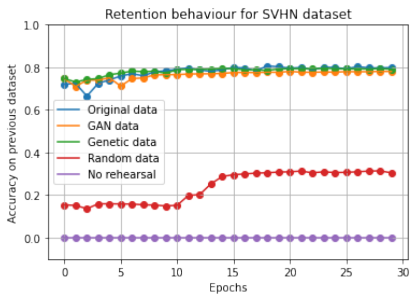


(d)

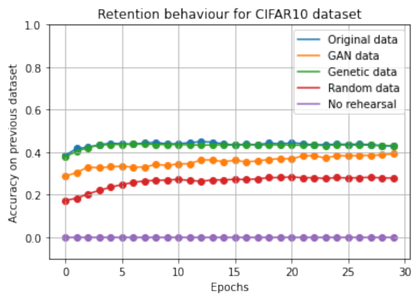
Fig. 2: Synthetic data generated using the proposed method. Figure (2a): original dataset. Figure (2b): Genetically generated samples. Figure (2c): Phase 1 Enrichment. Figure (2d): Phase 2 Enrichment



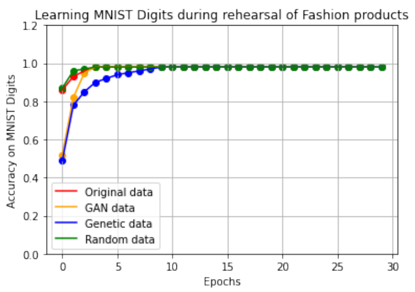
(a) Retention of Fashion dataset



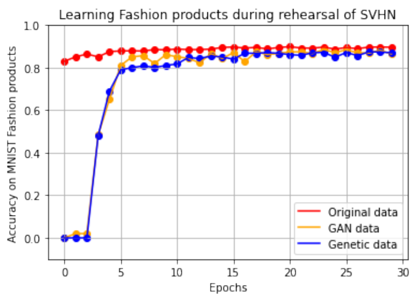
(b) Retention of SVHN dataset



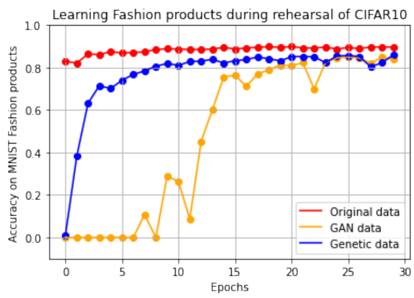
(c) Retention of CIFAR10



(d) Learning of MNIST digits during rehearsal of Fashion dataset.

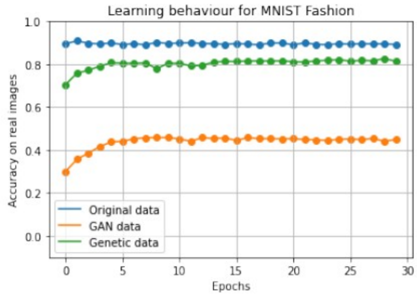


(e) Learning of MNIST Fashion during rehearsal of SVHN

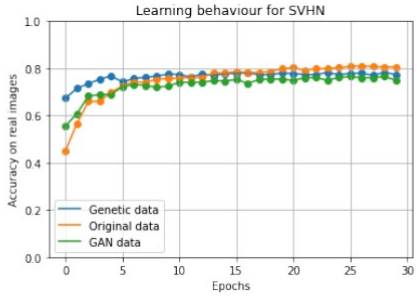


(f) Learning of MNIST Fashion during rehearsal of CIFAR10

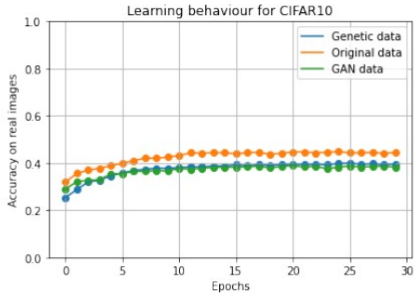
Fig. 3: The learning and retention behaviour of neural network under various rehearsal and pseudo-rehearsal schemes



(a) Classification accuracy on real fashion images

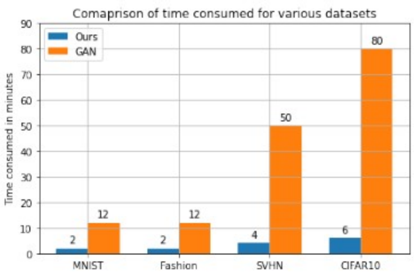


(b) Classification accuracy on real SVHN images

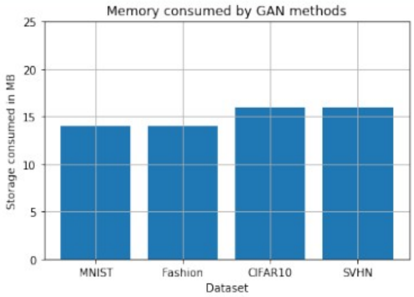


(c) Classification accuracy on real images of CIFAR10

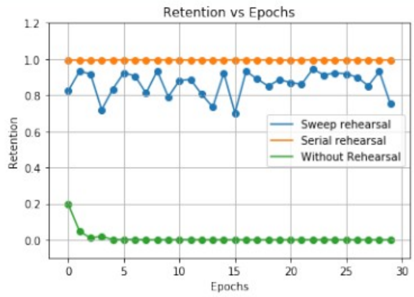
Fig. 4: Learning behavior of neural network while training on synthetic data.



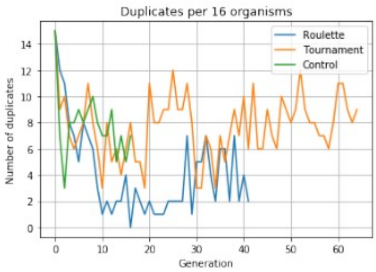
(a) Time required by all the methods



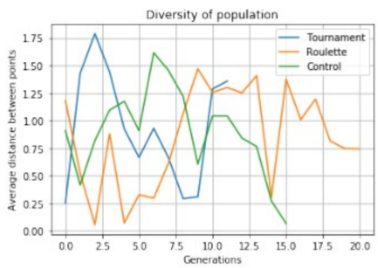
(b) Memory consumed by all the methods



(c) Comparison of rehearsal schemes



(d) Duplicate organisms for various selection schemes



(e) Distance between organisms for various schemes

Fig. 5: Results of Ablation studies and computational resource consumption comparisons

Dataset	GAN Data	Ours
MNIST Handwritten digits	**95.346%**	83.675%
SVHN	**86.8%**	83.6%
MNIST Fashion products	52.459%	**80.977%**
CIFAR10	55.7%	**61.8%**

TABLE I: Results of Agreement score experiment

Dataset	Genetic stage	Step 1	Step 2
MNIST Handwritten digits	44.55%	46.72%	89.36%
MNIST Fashion	50.56%	51.33%	81.36%
SVHN	7.3%	11.64%	76.86%
CIFAR10	16.16%	20.33%	42.14%

TABLE II: Results of Ablation study done on different stages of the proposed algorithm